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Dépendance Inter-Individuelle sur Panels Hétérogènes : Estimation, Inférence et Prévision

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Dépendance Inter-Individuelle sur Panels Hétérogènes :
Estimation, Inférence et Prévision

La disponibilité de données de panel ayant des dimensions temporelle et individuelle comparables et importantes augmente rapidement. Cette structure offre de nouvelles perspectives pour appréhender et caractériser les dépendances inter-individuelles. Cette thèse, tout en s'appuyant sur la littérature récente liée aux panels hétérogènes de grande taille en présence de dépendances inter-individuelles, en propose trois prolongements. Le premier chapitre traite des problèmes d'estimation, d'inférence et de prévision, en se concentrant sur la comparaison d'estimateurs hétérogènes, homogènes et partiellement homogènes en présence de dépendances inter-individuelles. Ces dernières renvoient à des structures de dépendance spatiale sur les perturbations et à la présence de facteurs communs. Le deuxième chapitre se focalise sur l'élaboration de tests robustes à différentes structures de dépendance inter-individuelle afin d'évaluer la qualité prédictive de plusieurs panels. Enfin, le troisième chapitre se concentre sur les prévisions, obtenues sur la base d'approches itérée et directe, et l'introduction de termes spécifiques liés aux dépendances inter-individuelles dans les prédicteurs. La comparaison des prévisions de taux d'inflation sur un panel de pays de l'OCDE révèle notamment l'importance de la prise en compte des facteurs communs.

Mots-clés : Dépendance Inter-Individuelle, Evaluation des Prévisions, Facteurs Communs, Tests d'Hypothèses, Panel Spatial.

Cross-Sectional Dependence in Heterogeneous Panels: Estimation, Inference and Forecasting

The availability of panel data sets with comparable and large time and individual dimensions is rapidly increasing. This structure offers new possibilities to understand and characterize cross-sectional dependence. This thesis makes three contributions to the recent literature dealing with large heterogeneous panel data sets with cross-sectional dependence. The first chapter deals with estimation, inference and forecasting issues focusing on the comparison of heterogeneous, homogeneous and partially homogeneous panel data estimators in presence of cross-sectional dependence modeled by spatial error dependence and common factors. In the second chapter novel tests for equal predictive ability in panels of forecasts are proposed, allowing for different types and strength of cross-sectional dependence across units. Finally, the third chapter focuses on forecasts obtained using iterated and direct methods. A special emphasis is put on the predictors which contain terms related to interactions between panel units. Inflation forecasts for the OECD countries are compared empirically. The results show the importance of taking common factors into account to predict inflation.

Keywords: Common Factors, Cross-Sectional Dependence, Forecast Evaluation, Hypothesis Testing, Spatial Panels.

Acronyms

BLUE Best Linear Unbiased Estimator 30

BLUP Best Linear Unbiased Predictor 36, 145

CCE Common Correlated Effects 34, 38

CD Cross-sectional Dependence 20, 21, 23, 25, 26, 32, 36, 37, 39, 44, 45, 47, 68, 78, 94, 101, 103, 108, 116, 122–124, 136, 137, 151–153

DGP Data Generating Process 20, 27

EPA Equal Predictive Ability 20, 24, 39, 40, 94, 95

GLS Generalized Least Squares 25, 29, 30, 36

HAC Heteroskedasticity and Autocorrelation Consistent 39

IMF International Monetary Fund 24, 39, 40, 95–98, 177

MAE Mean Absolute Error 38, 41, 96, 149, 160, 162

MG Mean Group 30, 38

OECD Organisation for Economic Co-operation and Development 20, 24, 26, 27, 37, 39, 40, 93, 95–99, 118, 120–124, 127, 174, 177

OLS Ordinary Least Squares 29, 30, 35

PC Principal Components 38, 39, 156

PCA Principal Components Analysis 34, 37, 40, 136

RMSE Root Mean Squared Error 38, 41, 96, 149, 160–165

SCD Strong Cross-sectional Dependence 21, 37, 39, 40, 44, 47, 62, 94, 105–111, 115, 117, 122, 124

SHAC Spatial Heteroskedasticity and Autocorrelation Consistent 39, 95

WCD Weak Cross-sectional Dependence 21, 37, 39, 44, 46, 47, 56, 57, 62, 80, 94, 103–111, 115, 122–124, 173

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Introduction

In the classical analysis of panel data it is assumed that the individual dimension of the data set is large whereas the time dimension is small and fixed. Hence, the theoretical properties of the estimation and testing procedures in panel data econometrics are explored by using asymptotics in the individual dimension which makes the analysis similar to the analysis of cross-sections. Although today it is still true for micro data sets that the time dimension is fairly small, the availability of panel data sets with comparable time and individual dimensions is rapidly increasing. This is true especially for macro data sets such as Penn World Tables, World Bank's World Development Indicators et cetera. These data sets cover more than 200 countries for the post-war period. Such micro data sets exist too. For instance, Panel Study of Income Dynamics (PSID) contains data on over 18,000 individuals followed for 60 years now.

There are several advantages of having such large data sets available for econometric analysis. First of all, more data points potentially bring more information, consequently, it is expected to be able to make more precise estimation, to draw more accurate inference and make better forecasts using these large panel data sets. Second, a long time dimension brings the possibility of distinguishing the long-run and short-run effects which has important implications for testing certain economic theories such as growth convergence, permanent income hypothesis et cetera.

In addition to extended possibilities, these data bring challenges together too. The first one is heterogeneity. In data sets where the interest lies on micro relations, it is hard to believe that a simple econometric model will be able to explain complex behaviors. It is usually true that each individual has some big or small deviations from a model implied by theoretical reasoning on a representative agent. Therefore, additional data points can make the analysis harder at times instead of bringing new information. This is related to the well-known "incidental parameters problem" (Neyman and Scott, 1948).

Secondly, in both macro and micro data sets units are related to each other, by implication, standard independent distribution assumption is usually is not satisfied. Two potential sources for this dependence exist: (i) one or more global factor which has an impact on each unit in the data set, (ii) a mechanism which connects the units in space such that closer units are more strongly correlated with each other.

This thesis makes an attempt to fill the gaps in the literature dealing with estimation, inference and forecasting issues in large heterogeneous panel data sets with cross-sectional dependence (CD). Throughout the thesis we use the term "large panel data" to refer to the data sets where both individual and time dimensions are large, theoretically infinite. These are sometimes called "data fields" (Quah, 1994) or "random fields" (Driscoll and Kraay, 1998).

The first chapter deals with estimation, inference and forecasting problems in this kind of data sets in a general framework. In this chapter the impact of CD on the performance of homogeneous, heterogeneous and partially heterogeneous estimators is investigated in presence of slope heterogeneity. In the second chapter a hypothesis testing issue is taken into consideration. Namely, the equal predictive ability (EPA) tests which became popular especially after the influential work of Diebold and Mariano (1995) have been generalized in a panel data framework. Finally, the third chapter goes further in the attempts to answer questions in forecasting. In this chapter, the optimal forecasting strategies using panel data explored using a quarterly data set from the Organisation for Economic Co-operation and Development (OECD) countries. Several dynamic panel data models and estimators are compared in terms of their predictive ability. In particular, the possibility of using global information to forecast unit specific outcomes is studied.

Related Literature. The thesis is related to three main areas in econometric literature on panel data: (i) heterogeneity, (ii) CD, and (iii) forecasting. Throughout the work, heterogeneity mainly refers to unit level heterogeneity such that the parameters of the underlying data generating process (DGP) depend on the individuals in the data set, however, when required, possible heterogeneity over time is also taken into account. By CD, correlation among the panel units is meant. Forecasting refers to the prediction of individual outcomes in a future date after the last observation in the data set. This is sometimes called "post-sample prediction" in contrast to "out-of-sample prediction" which is used for the prediction of values related to a panel unit which does not exist in the data set (Granger and Huang, 1997).

Heterogeneity has been a central theme in panel data econometrics since its emergence and now a large literature exists dealing with the topic. Important theoretical contributions to the area include Swamy (1970), Chamberlain (1982), Pesaran and Smith (1995), among others. In addition to these, a wide applied literature exists. For instance, Baltagi and

Griffin (1997), Baltagi et al. (2000, 2003, 2004) compared the results from the estimation of a common regression model using different homogeneous and heterogeneous panel data estimators. These early studies showed the importance of the question of heterogeneity in panel data analysis and the literature in the area keeps growing in several directions. More recently, Paap et al. (2015), Pesaran and Zhou (2018) also have dealt with the estimation of heterogeneous panels. The first study is concerned with the optimal estimation of slope parameters whereas the second one is on the implications of partial homogeneity of the constant term for the standard panel data estimators. This thesis contributes to this literature by considering other aspects of large panels simultaneously.

CD has been taken into consideration in two major ways in the literature. First is the spatial approach where local interactions between units are modeled with a spatial weight matrix. This approach is usually used to model weak cross-sectional dependence (WCD). The second one is the common factor approach where there are one or more variables which affect all units in the panel, potentially with a heterogeneous coefficient. This strategy suits better in modeling strong cross-sectional dependence (SCD). Some important work in the analysis of spatial panels include Driscoll and Kraay (1998), Conley (1999), Kapoor et al. (2007), Fingleton (2008), Yu et al. (2008). The common factor approach attracted attention especially for the analysis of macroeconomic panel data sets and major works in the area include Bai and Ng (2002), Bai (2003), Pesaran (2006), Bai and Ng (2008b), Bai (2009). This thesis benefits from these works and contributes to the area.

Forecasting with panel data is a rapidly growing area in econometrics. Several important studies have considered the possibility of using information from different units to improve the forecasts for individual quantities. Some examples are Garcia-Ferrer et al. (1987), Chamberlain and Hirano (1999), Hoogstrate et al. (2000), Canova and Ciccarelli (2004), Gavin and Theodorou (2005), Fok et al. (2005). Many studies have been conducted which combine the previous two areas with forecasting with panel data. For instance, the papers by Baltagi and Griffin (1997), Baltagi et al. (2000), Baltagi et al. (2000), Baltagi et al. (2003), Baltagi et al. (2004) have investigated the role of the choice between homogeneous or heterogeneous estimators on forecasting performance and Baltagi and Pirotte (2014), Baltagi et al. (2014) studied the optimal prediction under spatial dependence in panels. In this thesis, the role of the heterogeneous and homogeneous estimation, WCD and SCD taken into consideration simultaneously while studying forecasting with panel data.

Methodology. In this thesis theoretical knowledge and empirical devices are used in a complementary manner. Asymptotic theory provides an invaluable guidance in econometrics. In each part of the study a special emphasis is given to large sample properties of the estimation and testing procedures. Wherever the asymptotic theory is incomplete in the literature, these gaps are tried to be filled by the usage of analytical tools.

However, for the topics covered in this thesis either little or no theoretical knowledge is available up to date concerning the finite sample properties of the econometric methods required. Or most of the time, the analytical properties of the estimators, testing procedures and predictors are extremely hard to follow. Hence, computer experiments are required to understand how reliable are the procedures in practice and how they compare to each other. In each part of the thesis, Monte Carlo simulations are used to study the properties of econometrics tools under consideration.

Monte Carlo analysis comes with caveats too, however. Often the results from the Monte Carlo experiments are heavily dependent to the particular parameter values undertaken in simulations (Hendry, 1984). The obvious solution is to consider as many parameters as possible to see if the conclusions change as a consequence. This brings other problems: the risk of confirmation bias, the uncertainty on the completeness of the analysis, and computational difficulties. In the case that all theoretical knowledge available is used, the first two problems can be mostly avoided. For some of the procedures undertaken in this study, computational issues were posing some limitations. However, these limitations are kept at minimum.

In the first chapter of the study, the available knowledge on the analytical properties of the econometric methods used are documented and discussed. This analysis is complemented with an extensive Monte Carlo study using a general framework which is able to encompass recent most important contributions in the literature. To avoid any kind of bias, many different parametrization of the same process or several different processes are used to evaluate the econometric methods in question. For instance, to discover the small sample properties of recently proposed panel data estimators, a general model is formulated. This model has the property of being the one for which these estimators are created. Then deviations from this model's assumptions in several dimensions are analyzed. As estimation performance is not the only goal of applied econometrics, the robustness of the results is investigated with a forecasting exercise.

In the second chapter, some of the research questions arising from the previous chapter are targeted. Analytical properties of certain hypothesis testing procedures are documented, and again, the results are confirmed by means of Monte Carlo experiments. Also their limitations are investigated in these experiments. In this chapter an empirical example is given. In this empirical exercise, the novel procedures which are proposed are compared with the existing tools. This is a useful methodological approach as these existing tools are very well understood and largely studied in the literature.

In the third chapter a different but complementary methodology is followed. In this part, theoretical questions are tried to be answered using real data. An extensive empirical study is conducted to compare the performance of the novel and existing estimation, testing, and prediction procedures. Using out-of-sample forecasts, the results of the previous chapters are confirmed.

Contribution. The study contributes to the analysis of large panels in several ways. First of all, it has the quality of being the unique work which evaluates the properties of the most up to date econometric tools in a comparative manner. As discussed in detail below, an important methodological question in panel data analysis has been “to pool or not to pool” since the early 90’s (Maddala, 1991). In this study this question plays a central role. In each chapter the processes generating the data under consideration is assumed to be heterogeneous and econometric procedures are compared in terms of the success to deal with this situation.

In the first chapter, this is done by comparing heterogeneous, homogeneous and partially homogeneous estimators. Especially the last group of estimators is rarely compared in the literature; hence, this work contributes to this area. This chapter also contributes to the area of forecasting using heterogeneous panels with CD. A novel approach to forecasting using unobserved common factors is proposed and its small sample performance is evaluated.

The second chapter contributes to the area of forecast evaluation. The comparison made in the first chapter on forecast performance focuses on the differences in small sample properties of several estimators. In applied econometric work, formal tests are needed for comparing different procedures. In this chapter this problem is undertaken. Existing methods in this area are built for comparisons using a single time series, whereas for panel data little or no contribution has been made. This is interesting as several data sets are already available to be used to compare forecasts. Also increasing interest in forecasting with panel data requires formal procedures of forecast evaluation. This issue was briefly undertaken by Pesaran et al. (2009) with an obvious panel generalization of the Diebold and Mariano (1995) test. In this chapter several tests of EPA hypothesis are proposed taking into account the complications arising from using panel data. Another important contribution of this chapter is in terms of an application. Here, OECD and International Monetary Fund (IMF) economic growth forecasts are compared using these novel procedures. The existing literature in this area considered only simple forecast accuracy measures. Thus, this work fills an important gap in the literature.

The third chapter contributes to the literature on forecasting in several ways. First of all, to my knowledge this is the first study which compares direct and iterated forecasting methods using panel data. In time series literature, important studies which compare the two methods of forecasting exist (see, for instance, Marcellino et al., 2006), whereas for panel data no study has been conducted. Secondly, it adds to the literature by forecasting country specific series using global information by means of factor augmented time series models. The main objective here is to forecast inflation in OECD countries. Two inflation measures under consideration follow similar patterns in different countries. Consequently, the information common to different markets can increase our ability to set better forecasts. Third contribution is made by overcoming a technical difficulty on how to construct these common factors for forecasting and different possibilities are compared.

Analysis of Large Panels: Advantages and Challenges

Using panel data comes with advantages and challenges. An excellent review of the topic is undertaken by Hsiao (2007). In this subsection, I will focus on the issues specific to the analysis of large panel data sets. The main advantage of a large panel data set is that the increased number of total observations potentially provides more information. However, new data can bring less or no information if there are large deviations from the average relationships that are being interested in. I will focus on 4 issues: (i) time series analysis by pooling information on different units, (ii) data availability, (iii) heterogeneity, and (iv) asymptotic theory.

Time Series Properties and Dynamic Panels. An important aspect of economic relationships is that their nature changes in the short run and the long run. A long time series is required to analyze this kind of relationships. However, a single time series may not be able to provide the required information to make inference in certain situations. For instance, a panel data set provides the possibility of filtering out the movements in variables common to all individuals which is not feasible in a single time series case. If the stochastic processes which drive these common movements are correlated with the explanatory variables in a regression model, we risk having inconsistent estimates by using a single time series. Any panel data set will serve to remove these movements under certain conditions. However, if the time dimension is not large enough, it will be more complicated to distinguish between short-run and long-run relations. This is because this decomposition usually requires the estimation of a dynamic model but it is well known that usual within and generalized least squares (GLS) estimators provide inconsistent estimates in a dynamic panel data model with a small time dimension. This is known as the Nickell bias (1981). Phillips and Sul (2007) generalized the bias formulae to the panels which follow trends and involve CD.

In short panels seminal papers by Holtz-Eakin et al. (1988), Arellano and Bond (1991), Blundell and Bond (1998) provided the means of consistently estimating the autoregressive parameters. The estimators proposed utilize an instrumentation strategy to overcome the endogeneity problem arising from the correlation between the lagged dependent variables and the unit specific intercepts. Although they gained a lot of popularity, they have the disadvantage of relying on varying degrees of subjectivity, for instance, in the selection of the instruments, their weights et cetera. The number of instruments in these estimation procedures grows at the rate of T^2 where T is the number of time series observations. This creates a problem of downward bias in the estimation of the autoregressive parameter (Ziliak, 1997). As pointed out by Hsiao (2007), a solution to this problem is to use likelihood methods. However, this method involves new problems about the requirement of distributional assumptions on the initial observations of the dependent variable.

All these problems of the short panel data sets are automatically overcome with the availability of a large time series dimension. As in any panel data set, it is possible to remove the effects of the variables common to each unit in the panel by subtracting cross-sectional means, for instance. Furthermore, as time dimension goes to infinity, the Nickell bias disappears. Then it is possible to apply the techniques borrowed from time series analysis and utilize the advantages of the cross-sectional variation.

This advantage comes with the complication of needing extra care for potentially non-stationary panels. A wide literature has emerged in the analysis of non-stationary panel data starting with the important work of Quah (1994) on testing for unit roots using cross-sectional variation. Following this work, Maddala and Wu (1999), Choi (2001), Levin et al. (2002), Im et al. (2003) developed the toolbox of unit root testing with panel data in several dimensions, most importantly considering potential heterogeneity. A second generation of these tests also emerged by taking into account CD, see for instance Chang (2002), Breitung and Das (2005), Pesaran (2007). It is observed in the literature that the problems of distinguishing a unit root from a near unit root in the analysis of a single time series, that is, low power of the usual unit root tests, are vastly overcome with the usage of panels.

Another particularity of panel analysis of non-stationary time series is found to be on cointegration. In a single time series case, if two variables are integrated of order one but not cointegrated, the least squares estimator of the regression model involving them has a non-degenerate asymptotic distribution. This is called the spurious regression problem discovered first by Granger and Newbold (1974). Phillips and Moon (1999) and Choi (2001) showed that this is not the case for large panels. In fact, when the relative expansion of the number of observations in the individual dimension is sufficiently higher than the time series observations, the least squares estimator converges to the long-run relation between the two series.

Data Availability. In his review on panel data econometrics, Hsiao (2007) starts his discussion with the issue of data availability. There are now considerable amount of specialized data sets in a panel form, often even in a hierarchical structure. In the case of large panel data sets data availability can still be an important challenge. Of course, the main question here is "how big is big enough?" as usual (Tanaka, 1987). This is mostly an empirical question which can be answered only in the long run by accumulating knowledge by the usage of the methods developed and data in hand. However, following the results provided in this thesis and previous literature we can list some of the available data sets which can be considered.

On the macro side, as mentioned above, Penn World Tables (Feenstra et al., 2015) is an important example which has been widely used to study growth convergence theories. Choi (2006) used a sub-sample of this data set to test the unit root hypothesis in real GDP in OECD countries. His data set contains data on 23 countries for a period of around 30 years. This data set is usually combined with other macroeconomic data sets such as World Development Indicators by World Bank (see for instance Yanikkaya, 2003). As done by Choi (2006) often some sub-sets of world countries are used in econometric analysis for reasons of heterogeneity. If the focus is on the developed countries, a common sample is the OECD countries and the Economic Outlook of the organization provides information on hundreds of variables of member countries (OCDE, 2018). This publication contains both economic projections and historical data. Hence, it can be used in forecast comparison exercises too, as is done in this thesis. A final example is World Inequality Database created at the Paris School of Economics which contains information on top income shares in over 80 countries and the data sometimes covers the entire 20th century.

On the micro side, possibilities are more limited as it is much more costly to follow the micro units over time. One important example is PSID as mentioned above (Hill, 1992). This data set is used widely to explore the earnings dynamics over generations. EU KLEMS (Jäger, 2016) data set has a relatively disaggregated structure such that it covers industry level data for 25 industries in 28 countries, for over 20 years. IPUMS data (Ruggles et al., 2019) contains information in individual or household level starting from 1790's. More examples can be given.

Complex Heterogeneity of High Degree. The first law of geography is, as put by Waldo Tobler, "Everything is related to everything else, but near things are more related than distant things." This law sets the basis to spatial econometrics literature. Same principle directly applies to the issue of heterogeneity: all economic agents behave in a similar way, but near agents behave more similarly than distant agents. Bonhomme and Manresa (2015) reanalyzed the relationship between income and democracy following the influential paper by Acemoglu et al. (2008) taking into account possible heterogeneity. They found spatial patterns, or clustering, in both the unobserved components and the parameters in the regression model. Furthermore, this clustering can be attributed to several other characteristics of countries and not only geography itself. In this example, it is seen that geographical or economic remoteness can result in heterogeneity.

In large panel data sets which contain data from individuals of different socio-economic backgrounds, different countries, countries from different income groups, different continents, firms from different industries et cetera, heterogeneity in underlying DGP of the variables of interest is inevitable. The question is how much is known on this heterogeneity, how much new information is added by an additional observation. Boivin and Ng (2006) explored the issue in a forecasting study using factor models. Their results show that less data can actually be better for forecasting than using larger but noisy data.

When these complex types of heterogeneity, or non-stationarity, added in the time series dimension of the panel data the analysis becomes complicated. However, it brings new possibilities and new interesting questions too. This topic and the potential cure is discussed in the following subsection.

Complicated Asymptotic Theory. In the case of a single cross-section, the asymptotic theory for the usual estimators is simple, especially in the case of independently distributed error terms. The results from this case are almost immediately applicable to short panels, at least after standard transformation of a regression model. The limit theory for time series models where dependence is almost totally inevitable is more difficult. This is so especially in the case of non-stationary time series.

The complications in the time series limit theory are immediately carried to the analysis of large panels through the growing observation number in the time dimension. In addition to that, there is not a single way to derive the limiting distributions of estimators in large panels. Three approaches exist: (i) sequential limits, (ii) diagonal path limits, and (iii) joint limits. In the first one, usually the time series limit theory is first used to derive the asymptotic distributions, and the number of cross-sections is allowed to go to infinity after. In the second approach, one of the indexes is assumed to be a specific function of the other. In the last one, no functional dependence is assumed for the indexes and they are allowed to go to infinity simultaneously with no particular functional relation.

The main issue here is that there is no guarantee that these three approaches will give equivalent results for any problem in hand. Phillips and Moon (1999) gave the sufficient conditions for the equivalence of the sequential and joint limits but these seem to be hard to verify in practice and concerns only independently distributed cross-sectional units. Considering the potential dependencies, especially together with the uncertainties on how to model these dependencies, the theory becomes hard to follow.

Modeling Heterogeneity and Heterogeneous vs. Homogeneous Estimators

In previous subsection heterogeneity has been listed as an important aspect of large panel data sets. The question is hence, how to deal with it considering other aspects of such data sets. A large theoretical and applied literature exists which studies the optimal strategy to deal with the issue. This is mainly on the choice of the estimator in a static or dynamic panel regression model. If the interest lies on the average effects over cross-sectional units, can one pool the observations over these units or should separate analysis on each unit be applied first to average the estimates subsequently? If the second strategy is chosen should a specific weighting be applied or equal weights will serve as a good scheme?

In a seminal paper, Zellner (1969) provided some answers to these questions. He showed that by pooling data from heterogeneous micro units, it is possible to estimate the average effects over these units without bias. In Zellner's paper, by "pooling" the ordinary least squares (OLS) estimates are meant. So the weights are the inverse of the empirical second moments of the right hand side variables. Soon after, Swamy (1970) derived the GLS estimator of the average effects which uses a different (and optimal) weighting scheme.

Zellner's finding was important considering the question raised by Theil (1954) on empirical macro models: "Should not we abolish these models altogether?" His analysis provided support for macro econometric models. However, his analysis has its limitations. He believed that the results could be straightforwardly extended to models with lagged dependent variables. It turned out that this was not the case as shown by Pesaran and Smith (1995). Nevertheless, today we have all the tools required for the consistent estimation of average effects over micro units.

The common assumption behind the studies cited here is that the coefficients of the micro economic relations follow a certain probability distribution. This means that these results are more suitable in the cases where it is meaningful to assume that the units are randomly drawn from a common population. This assumption may not always be realistic in practical situations. In what follows, I first discuss the alternative of fixed coefficients assumption, and a possible extension which can bring these together, that is the correlated coefficients approach.

Fixed vs. Random Coefficients. A long lasting issue in the classical analysis of panel data is how to treat heterogeneous intercepts. Are they fixed parameters to be estimated or random variables which are drawn from a probability distribution? In the case of a large cross-sectional dimension and a small time dimension, treating the heterogeneous intercepts as fixed parameters causes a large loss of degrees of freedom. The GLS estimator proposed in the path-breaking work by Balestra and Nerlove (1966) overcomes this problem. In the GLS methodology, instead of estimating n intercepts, most of the time it suffices to estimate the second moment of the underlying distribution of random intercepts, hence, the number of parameters to be estimated is much smaller.

A similar problem arises in the case of heterogeneous slope coefficients. In a regression model for panel data set with a small to moderate time dimension, assuming that the slope coefficients are fixed parameters will have serious consequences because of the important loss in degrees of freedom. Especially in a complex model with several explanatory variables, assuming fixed coefficients will carry off all the advantages of having a panel data set. In fact, in this case it is most of the time required to estimate a separate regression model for each cross-sectional unit.

The solution is to assume that the unit specific coefficients are drawn from a common distribution. Hence, if the interest lies on the average effects over cross-sectional units, it will be enough to estimate the expected value of this common probability distribution. Swamy (1970) formulated the GLS estimator in a panel data set with random coefficients which is the best linear unbiased estimator (BLUE) of the average of the slope coefficients. The estimator requires a large T to estimate the variance components. An alternative is the so-called mean group (MG) estimator, first suggested by Chamberlain (1982). This is just a simple average of the individual OLS estimates of the slope coefficients. This second estimator gained a great popularity in especially applied literature mainly because of its simplicity. Also it is asymptotically equivalent to the GLS estimator of Swamy (Hsiao et al., 1998). It is intensively used in the works of Hashem Pesaran (see for instance Pesaran and Smith, 1995; Pesaran, 2006).

If the random coefficients assumption is suitable, these heterogeneous estimators provide the possibility of inferring to the average effects. However, they are naturally applicable only in the case of large panel data sets which are most of the time macroeconomic. In this kind of a data set where, for instance, cross-sectional units are countries, the random coefficients assumption does not look suitable as they are not randomly drawn from a common distribution. Furthermore, in a policy analysis exercise for instance, it is almost never the case that the average effect is the main interest. Instead, we are interested in the unit specific effects. In this case the ideal solution is to assume that the unit specific coefficients have a systematic and a random component. In regression models this is done by adding a number of nonlinear transformations of the explanatory variables in the model. In this thesis it is implicitly assumed that the model is correctly specified by the addition of these nonlinear terms and there is still a random component for which the researcher does not have the required information but can estimate its moments.[1]

Correlated Random Coefficients. An alternative to the fixed and random coefficients assumptions follows from the discussion of the last paragraph. In fact, the idea behind the addition of nonlinear combinations of the explanatory variables on the right hand side of a regression model comes from the –implicit or explicit– assumption of partial effects being functions of explanatory variables in the model or even other variables. Suppose that partial effects are determined by some variables which do not exist in the set of right hand side variables. If these variables are correlated with the regressors, simple homogeneous estimators are inconsistent for the average effects (Haque et al., 1999; Wooldridge, 2005; Sul, 2015). Hence, heterogeneous estimation has a certain advantage over the homogeneous estimation strategies.

A methodology which can be thought as a half way between homogeneous and heterogeneous estimators is to assume that some variables in the model has a homogeneous and

[1]For a methodological discussion and a defense of the random coefficient models the reader is referred to Swamy and Tavlas (1995).

others have heterogeneous coefficients. The estimation of such a mixed fixed and random coefficient model has been studied by Amemiya (1978) and an application can be found in Hsiao et al. (1989). This estimator uses the knowledge on the homogeneity of some of the coefficients so it is expected to be more efficient than the estimators assuming fully heterogeneous models. The econometric procedures used in this thesis can be generalized to suit to this kind of a model. The comparative efficiency from this kind of a strategy is a potential research question. Furthermore, if these gains important, it can be interesting to study how to test for the hypothesis of random but uncorrelated coefficients.

In general the choice between homogeneous and heterogeneous estimators is an example of the classical trade-off between bias and variance. While estimating too many parameters causes high variance, not being able to properly account for the heterogeneity in the underlying processes can cause bias. Combined with the interrelations between heterogeneity and CD, the heterogeneous vs. heterogeneous estimation remains as an important question in panel data econometrics.

Modeling Cross-Sectional Dependence

In time series analysis, it is almost always assumed that the random variables are correlated over time. Independence is rarely assumed, only after suitable transformations of the processes. This is most of the time the case in panel data econometrics too. The estimators of Holtz-Eakin et al. (1988), Arellano and Bond (1991), Blundell and Bond (1998) were specially built for short panels with lagged dependent variables, several different ways of correcting the variance estimates of typical estimators are proposed (see, for instance, Arellano, 1987; Driscoll and Kraay, 1998; Moscone and Tosetti, 2012), and a vast literature has focused on testing for residual autocorrelation (see Born and Breitung, 2016, and references therein).

This is only one of the (at least) two dimensions of a panel data set. Until recently, most of the studies in panel data econometrics assumed that the observations from different units are generated (or drawn from a population) independently. In neither macro nor micro econometrics we can expect the independence assumption to hold automatically. The question is how to model these dependencies, so that we can transform the variables under consideration, and obtain observations at least approximately independent. Two approaches to modeling CD exist: the spatial approach and the common factor approach. In what follows I discuss the exclusive aspects of these two approaches and their application in the analysis of large panel data sets.

Spatial Modeling. Statistical analysis of the interrelations of random variables in space has originated from the seminal paper by Whittle (1954). He extended the analysis of a univariate time series to the plane. The extension is non-obvious: in the case of time series, observations have a natural ordering whereas in space this is not the case. The notions of past and future apply; dependencies occur only in one direction that is from past to present and future. In the plane this is not the case. Because of the bidirectional dependencies, Whittle used spectral methods to develop estimators of the parameters in a simple spatial autoregressive model. The issue of spatial correlations became much more visible with the path-breaking studies of Cliff and Ord (1972, 1973). They extended the application of Moran (1950)'s I to detection of spatial correlations in regression errors which became almost a standard tool in the regression analysis with regional data.

The early contributions to spatial econometrics focused on urban and regional modeling. It is increasingly realized that spatial interactions are as important in macro econometrics. For instance, Conley and Ligon (2002) decomposed the spatial covariances of the long-run growth rates across countries into the portion explained by the countries' own characteristics and the one determined by the spatial spillovers. Using both geographic and economic distances, they showed the importance of these spillovers in the determination of long-run growth rates. Another example is the influential paper of Ertur and Koch (2007). The authors generalized the neoclassical growth model (Solow, 1956, 1957; Mankiw et al., 1992) with technological spillovers and showed evidence that these spillovers are present in the data.

These examples, besides a great number of other studies which can be mentioned, show the importance of the consideration of spatial dependencies in large panel data sets. In the econometric literature it becomes more and more common to allow spatial dependencies either implicitly or explicitly. A few studies which are most closely related to this thesis can be mentioned here. Pesaran and Tosetti (2011) who generalize the analysis of Pesaran (2006) consider spatial correlations in the error terms of large heterogeneous panels. Bai

(2009) allows correlations in the error terms but did not impose a particular spatial model on them. Likewise, Bonhomme and Manresa (2015) derived the asymptotic properties of their partially heterogeneous estimators under spatial error correlations. The common aspect of these papers is that they take spatial correlation as of secondary importance. In the paper by Aquaro et al. (2015) the interest lies directly on spatial spillovers. The authors generalize the standard spatial autoregressive models by allowing for heterogeneous coefficients.

Spatial dependence or spatial spillovers are closely related to another approach of studying correlations between panel units, namely the common factors. This approach is discussed in what follows.

Common Factors. The usage of common factors has gained an enormous popularity with the important contributions of Stock and Watson (1999, 2002a,b) to the forecasting literature. Their approach is based on augmenting time series predictive regressions using a few common factors embedded in a large number of indicators. Following these seminal studies, a great number of other researchers provided evidence on the empirical usefulness of their methodology. Here pure factor models will be mentioned briefly but the rest of the discussion will be left to the next subtitle on forecasting using panel data.

Suppose that we have a cross-section sampled from n dependent units. The covariance matrix of these n variables contain $n(n-1)/2$ covariance terms and, in the case of heteroskedasticity, n variance terms. Clearly, it is not possible to estimate all these entries in the covariance matrix using n observations. The existence of panel data can make the situation easier but does not solve the problem if the number of time series observations is not much larger than the number of units. Spatial modeling is one way to reduce the number of parameters to be estimated to construct an empirical covariance matrix.

In the case of panel data, an alternative approach is to suppose that the correlations among the units are driven by a small number of common factors. If these common factors are observed, the calculation of the sample covariance matrix is straightforward. In the case that they are unobserved, they have to be estimated from data. The literature dealing with common factors in panel data can be divided into two broad categories in terms of the methods of estimating the unobserved common factors. First one is the asymptotic principal components analysis (PCA) method and the second one is the methods using cross-sectional averages of observed variables as proxies for the common factors. This second approach is usually called the "common correlated effects (CCE)".

In traditional multivariate statistics it is assumed that the number of cross-sectional units n is small relative to the number of time series observations T, and the common factors are estimated using maximum likelihood approach (see, for instance, Anderson, 1984). When n is large and theoretically infinite, the number of parameters to be estimated gets large and makes the maximum likelihood nonoperational. In a static factor model, Stock and Watson (1998) were first to consider estimating the common factors using PCA considering large n. Ever since, PCA became an increasingly popular tool in the analysis of panel data.

The PCA approach is used mainly by Coakley et al. (2002), Bai (2009) and Song (2013). Their estimators based on estimation of common factors from the residuals of the panel data model. The CCE approach is based on the observation that by aggregating over units, it is possible to approximate the factors common to them, see Granger (1987), Forni and Reichlin (1996). Pesaran (2006) shows, in a large panel data setting, that cross-sectional averages of dependent variable and explanatory variables can be used as observable proxies in order to estimate the slope parameters consistently. Westerlund and Urbain (2015) provide an analytical comparison of these two methods.

This literature plays an important role in this thesis. Namely, in each chapter the possibility of having simultaneously common factors and spatial dependence is considered. The two approaches are compared theoretically, using Monte Carlo simulations and also real data.

Forecasting Using Panel Data

In the case of heterogeneous and randomly distributed slope coefficients, OLS is the best linear unbiased predictor of the individual coefficients under usual assumptions (Swamy, 1970). This makes it optimal (in mean squared sense) for forecasting. If the individual OLS is optimal, what can be the advantage of using panel data for forecasting unit specific quantities?

I discuss the possibility of improving individual forecasts using global information under three subtitles. First one is the bias-variance trade-off embedded in the issue of heterogeneous vs. homogeneous estimation of panel models. The evidence which is discussed below shows that, even in the case of heterogeneous panels, there can be an advantage of pooling when the objective is to forecast unit specific outcomes. Second, in spatial panels with random effects, the optimal predictor takes a special form due to Goldberger (1962) which opened an important area to itself within the panel forecasting literature. Third, the factor forecasts which gained an enormous popularity in time series literature are easily extended to the panel context.

Heterogeneous vs. Homogeneous Forecasts. One way to exploit the information coming from different cross-sectional units is to pool the data to estimate a common slope coefficient or -in the case of heterogeneous and random coefficients- the expectation of the distribution of them. If the slope coefficients are homogeneous, pooling estimators have lower variance than the heterogeneous estimators. However, under heterogeneity, they are biased for the unit specific coefficients. Hence, the question of pooling is an example of the bias-variance trade-off.

A large empirical literature compared different estimators in terms of their predictive ability. Some of the important studies are Baltagi and Griffin (1997), Baltagi et al. (2000), Baltagi et al. (2003), Baltagi et al. (2004). The common finding in these papers is the superiority of homogeneous estimators. Mark and Sul (2012) studied the comparison between homogeneous and heterogeneous estimators in terms of their forecast performance both analytically and empirically. They showed that the potential gain from pooling is a function of the degree of heterogeneity in the parameters of the right hand side variables in the predictive model. Their empirical application on the exchange rate forecasts confirmed this theoretical finding.

In this thesis, the comparison is studied both with simulation exercises and real data sets. It is confirmed that the heterogeneous estimators are much superior to homogeneous estimators when the number of time series observations per unit is large and the heterogeneity in the model parameters is strong. Furthermore, the topic is taken into consideration simultaneously with the case of CD.

Best Linear Unbiased Prediction. When the slope parameters of a panel data model are homogeneous, and the heterogeneous intercepts are fixed parameters, the optimal prediction of the dependent variable for each panel unit is constructed using the within estimator of the slope coefficients. In the case of random coefficients this is not the case for two reasons. First, in the random effects model the best linear unbiased estimator of the slope parameters is the GLS. The within estimator is less efficient, hence, it produces less accurate forecasts. Second, the random effects introduce autocorrelation in the error terms. This means that the estimation of the systematic part of the model does not provide an optimal predictor.

In this situation the best linear unbiased predictor (BLUP) of the future values of the variable of interest takes a special form which is first derived by Goldberger (1962). First it uses the GLS estimates of the slope parameters. Second and more importantly, it adds a portion of the averages of the GLS residuals in the prediction. As shown by Baltagi and Li (2004), in the case of spatial correlation, this means that the residuals from all units in the panel data set contributes to the prediction of each single unit. Hence, the global information proves useful in the prediction of unit specific outcomes.

Factor Forecasts. Can we improve individual forecasts using global data in an unrestricted, more general way than the spatial approach? Kopoin et al. (2013) has tried to answer this question using empirical forecasts of the Canadian regional growth rates. They showed that the forecasts using national and international information are significantly better than those which use only regional information. Engel et al. (2015) used data from several OECD countries to improve the forecasts of exchange rates of individual countries. Their approach is similar to that of Stock and Watson (1999). The difference is that in Stock and Watson (1999) the common factors are estimated from a large number of predictors, whereas Engel et al. (2015) estimate the common factors from a large number of countries. In this thesis, this possibility is further questioned, using both extensive Monte Carlo simulations and with empirical applications.

Lastly, it should be noted that there is a direct connection between the spatial approach and the common factor approach to forecasting. As discussed above, in the spatial approach the forecasts of a specific unit is made using a portion of the realizations of the random variables belonging to other units in the panel data set. As empirical common factors (estimated either using maximum likelihood or PCA) are weighted averages of the variables of interest, there is a strong connection between the two approaches. Although it is not in the scope of this thesis, it should be mentioned that it can be useful to compare the relative performance of spatial models and common factor models in terms of their predictive ability.

Plan of the Thesis

The thesis comprises of three self-contained chapters. In what follows the background and aim of each chapter, the methods used in them, and their main results are summarized.

Chapter 1: Heterogeneity and Cross-Sectional Dependence in Panels. The first chapter deals with estimation, inference and forecasting problems in large, heterogeneous panel data sets with different types of cross-sectional dependence (CD).

Background and Objectives: The main aim of this chapter is to investigate the impact of weak cross-sectional dependence (WCD) and strong cross-sectional dependence (SCD) on the performance of heterogeneous and homogeneous estimators in presence of low and high degrees of heterogeneity. In this chapter, a general heterogeneous panel data model which includes simultaneously unobserved common factors and spatial error dependence is presented. The associated estimation procedures are documented and a novel forecasting method for the panel data models with unobserved common factors is proposed.

Methods: By means of simulations, the estimation, inference and forecasting performance of 16 estimators is evaluated. The estimators taken into account are mainly connected to the papers by Swamy (1970), Pesaran (2006), Kapetanios and Pesaran (2007), Bai (2009), Song (2013), Bonhomme and Manresa (2015) and Su et al. (2016). These estimators comprise of heterogeneous, homogeneous and partially heterogeneous estimators. The performance of these estimation and forecasting procedures are compared by means of an extensive Monte Carlo exercise. The simulation framework is held in a level that is general enough to encompass recent important contributions in the panel data literature.

Results and Conclusions: The main results of this chapter can be summarized as follows: (i) Even for small T and n, heterogeneous estimators, especially the mean group (MG) estimator based common correlated effects (CCE) method of Pesaran (2006) and the MG estimator based on the iterative principal components (PC) approach of Bai (2009) and Song (2013), outperform their homogeneous counterparts. However, most of the estimators considered show desirable small sample properties. (ii) The dominance of the heterogeneous estimators are more pronounced for the cases of high heterogeneity, as expected, and this main result holds for different degrees of spatial dependence and factor dependence as well. (iii) The main difference on the performance of the two methods of dealing with unobserved common factors, namely CCE and PC, occurs when we change from low to high spatial dependence; whereas changing from low to high factor dependence does not make a big difference in their comparative performance. The estimators based on PC methods are found to be more robust to spatial dependence. This result shows that both methodology work equally good against unobserved factors. (iv) Among the two estimators assuming a grouped structure of heterogeneity, the grouped fixed effects of Bonhomme and Manresa (2015) performs well in terms of bias and root mean squared error (RMSE); whereas the classifier Lasso of Su et al. (2016) based on CCE transformation gives less satisfactory results. The performance of the grouped fixed effects estimator improves as the number of groups assumed in the estimation increases. (v) The findings above are confirmed by the forecasting exercise. Namely, the forecast accuracy of heterogeneous estimators measured by mean absolute error (MAE), RMSE, Theil's U statistic is better than their homogeneous counterparts.

Chapter 2: Equal Predictive Ability Tests for Panel Data. In the second chapter a hypothesis testing issue is taken into consideration. The equal predictive ability (EPA) test of Diebold and Mariano (1995) is generalized to panel data sets with heterogeneity and CD.

Background and Objectives: The main aim of this chapter is to propose tests for the EPA hypothesis for panel data taking into account both the time series and the cross-sections features of the data. Novel tests of EPA are proposed allowing to compare the predictive ability of two forecasters, based on n units, hence n pairs of time series of observed forecast errors of length T, from their forecasts on an economic variable.

Two types of tests of EPA are developed. The first one focuses on EPA on average over all panel units and over time. This test is useful and of economic importance when the researcher is not interested in the differences of predictive ability for a specific unit but the overall differences. In the second type of tests, to deal with possible heterogeneity, the focus has been put on the null hypothesis which states that the EPA holds for each panel unit.

Methods: An exploratory analysis on the historical forecast errors of the Organisation for Economic Co-operation and Development (OECD) and the International Monetary Fund (IMF) is conducted. This analysis and the previous literature suggest some stylized facts about the forecasts made by the two organizations: (i) Common Factors: the forecast errors of different countries are affected by common global shocks, (ii) Spatial Interactions: for countries which are closer to each other the comovement of the forecast errors are stronger, and (iii) Heterogeneity: international agencies make systematic errors for some particular groups of countries. The tests are developed to reflect these properties observed in the data.

To deal with WCD and SCD, the recent literature on PC analysis of large dimensional factor models (Bai and Ng, 2002; Bai, 2003) and covariance matrix estimation methods which are robust to spatial dependence (Kelejian and Prucha, 2007) have been followed.

The small sample properties of the tests proposed are investigated via an extensive Monte Carlo simulation exercise. In a time series framework the small sample properties of heteroskedasticity and autocorrelation consistent (HAC) estimators are well-known and comparison of the role of different kernel functions in the estimation performance is readily available (see Andrews, 1991). Whereas, in spatial modeling the Monte Carlo analysis on spatial heteroskedasticity and autocorrelation consistent (SHAC) estimators is limited to only the work of Kelejian and Prucha (2007). In this chapter, their analysis is extended in several dimensions, such that we consider many different combinations of time and cross-sectional dimension sizes and allow for several different kernel functions to investigate their role on small sample properties of the EPA tests.

Results and Conclusions: The small sample properties of the proposed tests have been found to be satisfactory in a large set of Monte Carlo simulations. In particular, the tests which are robust to SCD are found to be correctly sized in all experiments. This is the case even in the experiments which do not involve common factors but only spatial dependence. However, their power is generally low compared to test statistics which are robust only to spatial dependence, given that forecast errors do not contain common factors. In these cases, the Monte Carlo evidence suggests to use Bartlett and Parzen kernels for correctly sized test.

In the empirical application, it is found that IMF has an overall better performance in terms of bias whereas OECD makes predictions with less variance. However, the differences are rarely statistically significant. In a sub-sample of G7 countries OECD predictions are found to be superior to that of IMF.

Chapter 3: Multistep Forecasts with Factor-Augmented Panel Regressions. The third chapter goes further in the analysis on panel data forecasting. It contains an extensive empirical comparison of several models and methods of panel data in terms of their forecasting ability.

Background and Objectives: In this chapter, the optimal forecasting strategies using a general dynamic heterogeneous panel predictive regression model is explored. The model under consideration allows predicting unit specific outcomes with global common factors in macroeconomic variables. The main aim is to propose and compare forecast methods using such panels with unobserved common factors. Empirical iterated and direct forecasts are compared using two different forecasting approaches developed for panels with common factors. The first one uses estimates of the common factors in the predictive model by applying principal components analysis (PCA) on the residuals from a first stage consistent estimation of the slope coefficients. The unobserved nature of the common factors requires forecasting the future values of these estimated factors first, then computing the predictions on the variable of interest in a following step. In the second approach, the common factors are estimated from a number of auxiliary variables as in the works of Stock and Watson (2002a) and Bai and Ng (2006). The difference between these studies and used in this chapter is that here, common factors are estimated from the realizations of the same variable for different panel units whereas in their studies these factors come from a large number of indicators for the same panel unit. Although, the approach does not rule out the possibility of having several variables correlated with the common factors.

Methods: This chapter uses empirical forecasts to compare the properties of different methods and estimators. For this purpose, the data set is divided into an estimation and a prediction period. Mainly, the out-of-sample forecasting methodology of Marcellino et al. (2006) is followed. Two different accuracy measures are used: the RMSE and the MAE.

The comparison is done by comparing the distribution of these statistics over countries in the sample.

Results and Conclusions: The results showed that the direct method outperforms the iterated strategy in almost all cases. Comparison of the models with and without global common factors showed a clear dominance of the methods using global information in forecasting country specific variables. Finally, heterogeneous estimators of the slope parameters are found to outperform the homogeneous estimators in simple models. For large and more complex models, pooling has advantages for forecasting purposes.

Chapter 1

Heterogeneity and Cross-Sectional Dependence in Panels[1]

In this chapter, we focus on the comparison of heterogeneous and homogeneous panel data estimators in presence of cross-sectional dependence modeled by spatial error dependence, common factors or both. These specifications allow us to consider weak cross-sectional dependence (connected to a spatial weight matrix) and strong cross-sectional dependence (common factors). The estimation procedures are described and a forecasting approach is proposed in the presence of unobservable common factors. An extensive Monte Carlo study is conducted using a general framework able to encompass recent seminal contributions in the literature. The results show that even for small individual and time dimensions heterogeneous estimators perform better in terms of bias, RMSE, size and size adjusted power of two-sided tests. Statistical accuracy measures also confirm that the best forecasts are associated to heterogeneous estimators.

[1]This chapter is based on two papers written with Alain Pirotte and Giovanni Urga submitted to Revue d'Economie Politique and International Journal of Forecasting.

1.1 Introduction

For panel data studies with large n and fixed T, as is typical in micro panels, it is usual to pool the observations (Baltagi et al., 2008). In this case, standard estimators such as fixed effects (FE) and random effects (RE), appear as the only viable alternative. These estimators are based on two crucial assumptions: (i) slope homogeneity and (ii) cross-sectional independence. In data sets with large n and large T neither of these assumptions are expected to hold.

It is now well known that pooling in presence of slope heterogeneity can produce misleading results on the magnitude of the average effects and inference based on them. In a random coefficients model, average effects can be estimated consistently by pooled estimators with strictly exogenous regressors. However, in a seminal paper Pesaran and Smith (1995) show that the pooled estimators are not consistent for the average effect if the model contains weakly exogenous regressors.

Depending on its strength and nature, cross-sectional dependence (CD) can have similar consequences. Is it a result of local interactions generating spatial spillover effects or common factors which affect different units (see Chudik et al., 2011; Sarafidis and Wansbeek, 2012; Chudik and Pesaran, 2015; Bailey et al., 2016, and references therein)? The factor and spatial econometric approaches tend to complement one another, with the factor approach being more suitable for modeling strong cross-sectional dependence (SCD) (for instance aggregate common shocks), and the spatial approach (connected to a spatial weighted matrix) generally requiring weak cross-sectional dependence (WCD), as defined in Sarafidis and Wansbeek (2012).

In terms of their effects on the statistical properties of panel data estimators, the two types of CD can differ dramatically, therefore it is necessary to analyze them in a comparative way. The main aim of this chapter is to assert the impact of WCD and SCD on the performance of heterogeneous and homogeneous (pooled) estimators in presence of low and high degree of heterogeneity. An extensive Monte Carlo exercise is conducted using a general framework able to encompass recent seminal contributions in the literature such as, among others, Pesaran (2006), Bai (2009) and Pesaran and Tosetti (2011). It allows to study the impact of WCD and SCD on the performance of heterogeneous and homogeneous (pooled) estimators in presence of low and high degree of heterogeneity. The estimators that we evaluate are mainly connected to Swamy (1970), Pesaran (2006), Kapetanios and Pesaran (2007), Bai (2009), Song (2013), Bonhomme and Manresa (2015) and Su et al. (2016).

Our results indicate that heterogeneous estimators perform better than the pooled ones even when time and individual sample sizes are small. The performance is measured by evaluating the bias and the RMSE of slope parameter estimates, and also by investigating the size and the size adjusted power of two-sided tests which concern slope coefficients based on the alternative estimators.

In addition to the problem of estimating the parameters of interest, a way to investigate the estimation strategy is to study the forecasting accuracy of different models under various circumstances, using Monte Carlo simulations, in the spirit of Trapani and Urga (2009). A forecasting approach is proposed considering the presence of unobservable common factors which allows us to evaluate the accuracy of forecasts obtained from heterogeneous and homogeneous estimators. We use statistical accuracy measures, such as the root mean square error (RMSE) and Theil's U statistic, to study the performance of alternative estimators. The results indicate the predominance of forecasts associated to heterogeneous estimators.

The chapter is organized as follows: In Section 1.2, we present the heterogeneous panel data setup including simultaneously common factors and spatial error dependence. The associated estimation procedures are also summarized and the forecasting approaches are described. Section 1.3 deals with an extensive Monte Carlo study including the design of experiments, the discussion of estimation and forecasting results. Section 1.4 summarizes the main findings and provides some guidelines for future research.

1.2 Heterogeneous Panel Data Models

In this chapter, we consider stationary static panel data models with a CD structure in the disturbances. We use the following general heterogeneous panel data model with common factors and a spatial error dependence under different constraints

$$y_{it} = \boldsymbol{\alpha}_i'\mathbf{d}_t + \boldsymbol{\beta}_i'\mathbf{x}_{it} + \boldsymbol{\gamma}_i'\mathbf{f}_t + u_{it}, \tag{1.1}$$

$$\mathbf{x}_{it} = \mathbf{A}_i'\mathbf{d}_t + \boldsymbol{\Gamma}_i'\mathbf{f}_t + \mathbf{v}_{it}, \tag{1.2}$$

with

$$u_{it} = \rho_i \sum_{j=1}^{n} w_{ij}\xi_{jt} + \varepsilon_{it}, \tag{1.3}$$

where $i = 1, 2, \ldots, n$ and $t = 1, 2, \ldots, T$, y_{it} is the dependent variable for individual i at time t, $\mathbf{x}_{it} = (x_{i1t}, x_{i2t}, \ldots, x_{ikt})'$ is a $(k \times 1)$ vector of observed individual-specific regressors on the ith individual at time t, $\boldsymbol{\beta}_i = (\beta_{i1}, \beta_{i2}, \ldots, \beta_{ik})'$ are the corresponding $(k \times 1)$ slope parameters to be estimated. ρ_i are the spatial autoregressive parameters. $\mathbf{f}_t = (f_{1t}, f_{2t}, \ldots, f_{mt})'$ is a $(m \times 1)$ vector of unobservable common factors, $\boldsymbol{\gamma}_i = (\gamma_{i1}, \gamma_{i2}, \ldots, \gamma_{im})'$ is the associated $(m \times 1)$ vector of factor loadings. $\mathbf{d}_t$ is a $(l \times 1)$ vector of observable common factors with $(l \times 1)$ factor loadings $\boldsymbol{\alpha}_i = (\alpha_{i1}, \alpha_{i2}, \ldots, \alpha_{il})'$. $\mathbf{A}_i$ is the $(l \times k)$ matrix of factor loadings associated with the observable common factors and $\boldsymbol{\Gamma}_i$ is the $(m \times k)$ matrix of factor loadings of the unobservable common factors. The vector error process $\mathbf{v}_{it}$ is allowed to be autocorrelated and can contain WCD. The number of unobservable common factors, m, is supposed to be fixed, in particular m is assumed to be strictly smaller than n.

The error u_{it} is assumed to follow a spatial pattern. If ξ_{jt} denotes a zero mean random component, uncorrelated with ε_{it} and the components of (1.1), this process is the so-called spatial error component (SEC) process. If $\xi_{jt} = u_{jt}$, we have a spatial autoregressive (SAR), if $\xi_{jt} = -\varepsilon_{jt}$, we have a spatial moving average (SMA) process. Focusing on the last two processes which are the most widely used in practice, (1.3) can be written in compact matrix form as

$$\mathbf{u}_{.t} = \mathbf{S}\boldsymbol{\varepsilon}_{.t}, \tag{1.4}$$

where $\mathbf{u}_{.t} = (u_{1t}, u_{2t}, \ldots, u_{nt})'$, $\boldsymbol{\varepsilon}_{.t} = (\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{nt})'$, and

$$\mathbf{S} = \begin{cases} (\mathbf{I}_n - \mathbf{R}\mathbf{W}_n)^{-1} & \text{if} \quad \xi_{jt} = u_{jt}, \\ \mathbf{I}_n - \mathbf{R}\mathbf{W}_n & \text{if} \quad \xi_{jt} = -\varepsilon_{jt}. \end{cases} \tag{1.5}$$

where ε_{it} is the idiosyncratic error term. Moreover, $\mathbf{R} = \text{diag}(\rho_1, \rho_2, \ldots, \rho_n)$, $\mathbf{I}_n$ is an identity matrix of order $(n \times n)$, and $\mathbf{W}_n$ is the spatial matrix with elements w_{ij}. The spatial weights collected in $\mathbf{W}_n$ are assumed to be non-stochastic. $\mathbf{W}_n$ is a $(n \times n)$ known spatial weights matrix which has zero diagonal elements and is usually row-normalized. The row and column sums of $\mathbf{W}_n$ are assumed to be uniformly bounded in absolute value. If $\mathbf{W}_n$ is defined as first order contiguity, such elements consist of location pairs that have a common border but there is no higher order contiguity. Overall, this means that $\mathbf{W}_n$ expresses the degree of connections between spatial units. In general, note that $\mathbf{W}_n$ and $(\mathbf{I}_n - \mathbf{R}\mathbf{W}_n)$ have to satisfy some regularity conditions, as given by Aquaro et al. (2015).

The structure of CD described above combines WCD and SCD. To illustrate the usefulness of combining these two types of CD, we may refer to cross country growth regressions. On the one hand, it is required to consider the SCD as it can be viewed as a result of a number of common factors that may have different effects on total factor productivity across countries. These include, for instance, aggregate technological shocks or oil price shocks that may affect total factor productivity through their effects on production costs. On the other hand, it is likely to have WCD as it can be viewed as a result of spatial spillover effects, for instance international technology diffusion which can be related to geographical distance due to transport costs or geographical barriers.

Specifications (1.1)-(1.3) represent a general formulation which nests several heterogeneous panel data models, with and without CD, connected to common factors (SCD) or to spatial spillover effects (WCD).

Another important feature of panel data we explore in this chapter is the heterogeneity. In the next section, we offer an overview of the heterogeneous models and the related estimation methods used in panel data econometrics.

1.2.1 Models without Cross-sectional Dependence

As already mentioned above, the homogeneity assumption of the slope coefficients is a hypothesis that is almost always rejected in practice, see Baltagi et al. (2008). For instance, changing economic structures or different socioeconomic and demographic background factors imply that response coefficients vary over time or are different across cross-sectional units. For more details see Hsiao and Pesaran (2008), Hsiao (2014). One of the crucial issues in panel data analysis is how the differences in behaviour across individuals or through time should be modeled. Assuming in (1.1)-(1.3) that the explanatory variables $\mathbf{x}_{it}$ are strictly exogenous, $\boldsymbol{\alpha}_i' = \mathbf{0}$, $\boldsymbol{\gamma}_i' = \mathbf{0}$, $\rho_i = 0, \forall i$,

$$\boldsymbol{\beta}_i = \boldsymbol{\beta} + \boldsymbol{\delta}_i, \quad \boldsymbol{\delta}_i \sim \text{IID}(\mathbf{0}, \boldsymbol{\Omega}_\delta), \quad i = 1, 2, \ldots, n, \tag{1.6}$$

where $\boldsymbol{\beta} = (\beta_1, \beta_2, \ldots, \beta_k)'$, $\boldsymbol{\delta}_i = (\delta_{i1}, \delta_{i2}, \ldots, \delta_{ik})'$, $\boldsymbol{\delta_i}$ are distributed independently of u_{jt} and $\mathbf{x}_{jt}$, $j = 1, \ldots, n$. This corresponds to the random coefficient model (RCM) popularized by Swamy (1970). Swamy's estimator (SW) of $\boldsymbol{\beta}$ is given by

$$\widehat{\boldsymbol{\beta}}_{SW} = \sum_{i=1}^{n} \mathbf{W}_i \widehat{\boldsymbol{\beta}}_i, \tag{1.7}$$

$$\widehat{Var}\left(\widehat{\boldsymbol{\beta}}_{SW}\right) = \left[\sum_{i=1}^{n} \left(\widehat{\boldsymbol{\Omega}}_\delta + \widehat{\boldsymbol{\Sigma}}_{\widehat{\beta}_i}\right)^{-1}\right]^{-1}, \tag{1.8}$$

where

$$\mathbf{W}_i = \left[\sum_{j=1}^{n} \left(\widehat{\boldsymbol{\Omega}}_\delta + \widehat{\boldsymbol{\Sigma}}_{\widehat{\beta}_j}\right)^{-1}\right]^{-1} \left(\widehat{\boldsymbol{\Omega}}_\delta + \widehat{\boldsymbol{\Sigma}}_{\widehat{\beta}_i}\right)^{-1}, \tag{1.9}$$

$$\widehat{\boldsymbol{\beta}}_i = \left(\mathbf{X}_{i.}'\mathbf{X}_{i.}\right)^{-1} \mathbf{X}_{i.}'\mathbf{y}_{i.}, \tag{1.10}$$

$$\widehat{\boldsymbol{\Sigma}}_{\widehat{\beta}_i} = \widehat{\sigma}_i^2 (\mathbf{X}_{i.}'\mathbf{X}_{i.})^{-1}, \tag{1.11}$$

and

$$\widehat{\sigma}_i^2 = \frac{1}{T-k} \mathbf{y}_{i.}'\mathbf{M}_i \mathbf{y}_{i.}, \tag{1.12}$$

$$\widehat{\boldsymbol{\Omega}}_\delta = \frac{1}{n-1} \sum_{i=1}^{n} \underline{\widehat{\boldsymbol{\beta}}}_i \underline{\widehat{\boldsymbol{\beta}}}_i' - \frac{1}{n} \sum_{i=1}^{n} \widehat{\boldsymbol{\Sigma}}_{\widehat{\beta}_i}, \tag{1.13}$$

with $\mathbf{M}_i = \mathbf{I}_T - \mathbf{X}_{i.} \left(\mathbf{X}_{i.}'\mathbf{X}_{i.}\right)^{-1} \mathbf{X}_{i.}'$, $\underline{\widehat{\boldsymbol{\beta}}}_i = \widehat{\boldsymbol{\beta}}_i - n^{-1} \sum_{i=1}^{n} \widehat{\boldsymbol{\beta}}_i$, $\mathbf{y}_{i.} = (y_{i1}, y_{i2}, \ldots, y_{iT})'$, $\mathbf{X}_{i.} = (\mathbf{x}_{i1}', \mathbf{x}_{i2}', \ldots, \mathbf{x}_{iT}')'$. The variance estimator (1.13) can be non-positive definite. Thus, Swamy (1970) suggests to use the first part of (1.13) in practice. Swamy's estimator (1.7) is a weighted average of the least squares estimator for each cross-sectional unit.

An alternative to Swamy's estimator is the mean group (MG) estimator, suggested by

Chamberlain (1982). This has also been used by Pesaran and Smith (1995) in the context of dynamic heterogeneous panel data models. It is defined as

$$\widehat{\boldsymbol{\beta}}_{MG} = \frac{1}{n}\sum_{i=1}^{n}\widehat{\boldsymbol{\beta}}_i, \tag{1.14}$$

and

$$\widehat{Asy.Var}\left(\widehat{\boldsymbol{\beta}}_{MG}\right) = \frac{1}{n(n-1)}\sum_{i=1}^{n}\underline{\widehat{\boldsymbol{\beta}}}_i\underline{\widehat{\boldsymbol{\beta}}}_i'. \tag{1.15}$$

Eq. (1.14) corresponds to the simple average of OLS estimator of each cross-sectional unit.

SW and MG estimators are based on the assumption that each cross-sectional unit has its own slope parameter $\boldsymbol{\beta}_i$. Recently, Sarafidis and Weber (2015), Bonhomme and Manresa (2015), Su et al. (2016), among others, have considered the possibility of having clusters in the panel such that the slope parameters are homogeneous within groups but heterogeneous among them. The unit specific slope parameters are given by

$$\boldsymbol{\beta}_i = \sum_{g=1}^{K}\boldsymbol{\lambda}_g \mathbb{1}\{i \in G_g\}, \tag{1.16}$$

where K is the number of groups which is assumed here to be known and fixed, $\boldsymbol{\lambda}_g$ are the group specific parameters, G_g is the set of indexes of n_g units which belong to group g, $\boldsymbol{\lambda}_g \neq \boldsymbol{\lambda}_{g'}$, $\forall\ g \neq g'$, $\bigcup_{g=1}^{K} G_g = \{1, 2, \ldots, n\}$ and $G_g \cap G_{g'} = \emptyset$, $\forall\ g \neq g'$. The primary interest concerns the parameters $\boldsymbol{\lambda}_g$ and $\boldsymbol{\beta}_i$. Let's define $\boldsymbol{\beta}^n = (\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, \ldots, \boldsymbol{\beta}_n)$, $\boldsymbol{\lambda}^K = (\boldsymbol{\lambda}_1, \boldsymbol{\lambda}_2, \ldots, \boldsymbol{\lambda}_K)$, Su et al. (2016), relying on group Lasso literature, propose to use the Penalized Least Squares criterion function

$$\underline{Q}_{nT}(\boldsymbol{\beta}^n, \boldsymbol{\lambda}^K) = Q_{nT}(\boldsymbol{\beta}^n) + \frac{\phi}{n}\sum_{i=1}^{n}\prod_{g=1}^{K}||\boldsymbol{\beta}_i - \boldsymbol{\lambda}_g||, \tag{1.17}$$

where

$$Q_{nT}(\boldsymbol{\beta}^n) = \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}\left(y_{it} - \boldsymbol{\beta}_i'\mathbf{x}_{it}\right)^2, \tag{1.18}$$

and ϕ is a tuning parameter. The estimates of $\boldsymbol{\lambda}^K$ and $\boldsymbol{\beta}^n$ obtained by minimizing (1.17) are called the *C-Lasso* estimates. They suggest an iterative algorithm to compute these estimates. The numerical algorithm starts with some initial values of $\boldsymbol{\lambda}^K$, $\boldsymbol{\beta}^n$ and assigns each unit to all possible groups. The group which gives the minimum of the objective function is identified as the one that a unit belongs to and the estimates are updated accordingly. The procedure is repeated until numerical convergence. Su et al. (2016) show that, under strict exogeneity of the regressors,

$$\sqrt{n_g T}(\widehat{\boldsymbol{\lambda}}_g - \boldsymbol{\lambda}_g) \to N(\mathbf{0}, \mathbf{H}_{1,g}^{-1}\boldsymbol{\Omega}_{1,g}\mathbf{H}_{1,g}^{-1}), \tag{1.19}$$

where

$$\mathbf{H}_{1,g} = \lim_{n_g, T\to\infty} \frac{1}{n_g T} \sum_{i\in G_g} \sum_{t=1}^{T} E(\mathbf{x}_{it}\mathbf{x}_{it}'), \tag{1.20}$$

$$\boldsymbol{\Omega}_{1,g} = \lim_{n_g, T\to\infty} \frac{1}{n_g T} \sum_{i\in G_g} \sum_{t=1}^{T} \sum_{s=1}^{T} E(u_{it}u_{is}\mathbf{x}_{it}\mathbf{x}_{is}'). \tag{1.21}$$

1.2.2 Models with Common Factors

In reality, both in micro and macro applications units are correlated with each other in some way. If each unit is affected by these factors with the same order of magnitude, the standard two-way fixed effects ($2WFE$) model provide consistent estimates of the homogeneous slope parameters of observed idiosyncratic variables, see Baltagi (2013) among others. However, if units are affected by the common factors in a different way, standard estimators are potentially biased and inconsistent, see Pesaran (2006). To deal with this kind of situations, several methods are proposed in the literature. Ahn et al. (2001, 2013) propose GMM estimation, Roberston and Sarafidis (2015) suggest an IV approach, Phillips and Sul (2003) a *SUR-GLS* estimator, Kapetanios and Pesaran (2007), Bai (2009) use principal components analysis to extract common factors affecting individuals, whereas Pesaran (2006) uses cross-sectional averages of the observed variables as proxies for the unobserved common factors. This literature has been extended in several directions. Bai and Kao (2006), Bai et al. (2009), Kapetanios et al. (2011) consider estimation under non-stationarity, and Pesaran and Tosetti (2011) allow for general spatially correlated errors. For critical reviews of these studies, we refer to Sarafidis and Wansbeek (2012), Westerlund and Urbain (2015) and Hsiao (2017).

To better deal with the multiple common factors, two main methods were proposed in the literature. These are methods based on cross-sectional averages and methods based on principal components considered mainly in two seminal papers by Pesaran (2006) and Bai (2009), respectively, that we present in the next sections.

1.2.2.1 Estimating Common Factors Based on Cross-sectional Averages

This class of estimators is based on the observation that by aggregating over units, it is possible to approximate the factors common to them, see Granger (1987), Forni and Reichlin (1996). Pesaran (2006) shows, in a large panel data setting, that cross-sectional averages of dependent variable and explanatory variables can be used as observable proxies in order to estimate the slope parameters consistently. The author works on the estimation of the model given in (1.1) and (1.2) using the cross-sectional averages of the explanatory variables and the dependent variable as observable proxies for the unobserved common factors as $n \to \infty$. To see this, rewrite (1.1) and (1.2) as

$$\mathbf{z}_{it} = \begin{pmatrix} y_{it} \\ \mathbf{x}_{it} \end{pmatrix} = \mathbf{B}_i'\mathbf{d}_t + \mathbf{C}_i'\mathbf{f}_t + \mathbf{e}_{it}, \tag{1.22}$$

where

$$\mathbf{B}_i = \begin{pmatrix} \boldsymbol{\alpha}_i & \mathbf{A}_i \end{pmatrix} \begin{pmatrix} 1 & \mathbf{0} \\ \boldsymbol{\beta}_i & \mathbf{I}_k \end{pmatrix}, \mathbf{C}_i = \begin{pmatrix} \gamma_i & \boldsymbol{\Gamma}_i \end{pmatrix} \begin{pmatrix} 1 & \mathbf{0} \\ \boldsymbol{\beta}_i & \mathbf{I}_k \end{pmatrix}, \mathbf{e}_{it} = \begin{pmatrix} u_{it} + \boldsymbol{\beta}_i'\mathbf{v}_{it} \\ \mathbf{v}_{it} \end{pmatrix}.$$

Eq. (1.22) is a genuine factor model derived from (1.1) and (1.2).

Pesaran (2006) discusses the estimation of individual slope parameters in (1.1) and (1.2) and proposes different common correlated effects (CCE) estimators. For the individual slope coefficient, the CCE is given by

$$\widehat{\boldsymbol{\beta}}_{CCE,i} = \left(\mathbf{X}_{i.}'\overline{\mathbf{M}}_f\mathbf{X}_{i.}\right)^{-1}\mathbf{X}_{i.}'\overline{\mathbf{M}}_f\mathbf{y}_{i.}, \tag{1.23}$$

where

$$\overline{\mathbf{M}}_f = \mathbf{I}_T - \overline{\mathbf{H}}(\overline{\mathbf{H}}'\overline{\mathbf{H}})^{-}\overline{\mathbf{H}}'. \tag{1.24}$$

Here, $\bar{\mathbf{H}} = (\mathbf{D}, \bar{\mathbf{Z}})$, $\mathbf{D} = (\mathbf{d}_1', \mathbf{d}_2', \dots, \mathbf{d}_T')'$, $\bar{\mathbf{Z}} = (\bar{\mathbf{z}}_{.1}', \bar{\mathbf{z}}_{.2}', \dots, \bar{\mathbf{z}}_{.T}')'$ and $\bar{\mathbf{z}}_{.t}' = n^{-1}\sum_{i=1}^{n}\mathbf{z}_{it}'$. The CCE estimator uses observed common factors $\mathbf{d}_t$ and proxies constructed from cross-sectional averages of observed variables, $\bar{\mathbf{z}}_{.t}$, to achieve consistency in the estimation of individual specific slope parameters. Pesaran (2006) shows that this follows when $(n, T) \to \infty$ and if the following rank condition[2] on the factor loadings is satisfied

$$\operatorname{rank}(\bar{\mathbf{C}}) = m \leq k + 1, \tag{1.25}$$

where $\bar{\mathbf{C}} = n^{-1}\sum_{i=1}^{n}\mathbf{C}_i$. To derive the asymptotic distribution we also require that $\sqrt{T}/n \to 0$ as $(n, T) \to \infty$, with convergence rate being $\sqrt{T}$.

Once the individual specific parameters are computed using (1.23), we can infer their mean using these estimates. This is because the individual slope parameters follow the random coefficient model given in (1.6). Pesaran (2006) considers the MG estimator (1.14) which is just a simple average of the estimated individual slope parameters. This estimator is given by

$$\widehat{\boldsymbol{\beta}}_{CCEMG} = \frac{1}{n}\sum_{i=1}^{n}\widehat{\boldsymbol{\beta}}_{CCE,i}. \tag{1.26}$$

The estimator does not require $T \to \infty$ for consistency, it is consistent for fixed T and $n \to \infty$. As $(n, T) \to \infty$, it converges to a normal distribution at the rate of $\sqrt{n}$, its asymptotic distribution is determined by the distribution of the random slope parameters. We have

$$\sqrt{n}(\widehat{\boldsymbol{\beta}}_{CCEMG} - \boldsymbol{\beta}) \to N(\mathbf{0}, \boldsymbol{\Sigma}_{CCEMG}), \tag{1.27}$$

where $\boldsymbol{\Sigma}_{CCEMG} = \boldsymbol{\Omega}_{\delta}$.

Alternatively, one can use the fixed coefficients representation of the model to estimate the average effects directly. Under random coefficients assumption, the model (1.1) can be written as a fixed coefficient model as

$$\begin{aligned} y_{it} &= \boldsymbol{\alpha}_i'\mathbf{d}_t + \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\gamma}_i'\mathbf{f}_t + \epsilon_{it}, \\ \epsilon_{it} &= \boldsymbol{\delta}_i'\mathbf{x}_{it} + u_{it}. \end{aligned} \tag{1.28}$$

[2]See Karabiyik et al. (2017) for a discussion on this topic.

Then, we can use

$$\widehat{\boldsymbol{\beta}}_{CCEP} = \left(\sum_{i=1}^{n} \mathbf{X}_{i.}' \overline{\mathbf{M}}_f \mathbf{X}_{i.} \right)^{-1} \sum_{i=1}^{n} \mathbf{X}_{i.}' \overline{\mathbf{M}}_f \mathbf{y}_{i.}, \tag{1.29}$$

where $\overline{\mathbf{M}}_f$ is defined as in (1.24). If the regressors $\mathbf{x}_{it}$ are strictly exogenous, (1.29) is consistent. The estimator imposes homogeneity of the slope parameters, however its asymptotic distribution is centered around the true average effect $\boldsymbol{\beta}$ under the random coefficient assumption. The convergence rate is $\sqrt{n}$ which is slower than the usual $\sqrt{nT}$ of the homogeneous panel data estimators. Its asymptotic distribution is given by

$$\sqrt{n}(\widehat{\boldsymbol{\beta}}_{CCEP} - \boldsymbol{\beta}) \to N(\mathbf{0}, \boldsymbol{\Sigma}_{CCEP}), \tag{1.30}$$

where $\boldsymbol{\Sigma}_{CCEP} = \boldsymbol{\Psi}^{-1} \boldsymbol{\Xi} \boldsymbol{\Psi}^{-1}$,

$$\boldsymbol{\Psi} = \lim_{n\to\infty} \left(\frac{1}{n} \sum_{i=1}^{n} \boldsymbol{\Sigma}_{v_i} \right), \tag{1.31}$$

$$\boldsymbol{\Xi} = \lim_{n\to\infty} \left(\frac{1}{n} \sum_{i=1}^{n} \boldsymbol{\Sigma}_{v_i} \boldsymbol{\Omega}_{\delta} \boldsymbol{\Sigma}_{v_i} \right). \tag{1.32}$$

and $Var(\mathbf{v}_{it}) = \boldsymbol{\Sigma}_{v_i}$.

CCE estimators are based on the fact that cross-sectional averages of $\mathbf{z}_{it}$ can be used to remove the effect of common factors asymptotically. In general, cross-sectional averages of any subset of the elements of $\mathbf{z}_{it}$ provide similar results given that this subset satisfies the rank condition given above. In particular let us consider the estimator (1.23) with

$$\widetilde{\mathbf{M}}_f = \mathbf{I}_T - \widetilde{\mathbf{H}}(\widetilde{\mathbf{H}}'\widetilde{\mathbf{H}})^{-}\widetilde{\mathbf{H}}', \tag{1.33}$$

with $\widetilde{\mathbf{H}} = (\mathbf{D}, \overline{\mathbf{X}})$, $\overline{\mathbf{X}} = (\bar{\mathbf{x}}_{.1}', \bar{\mathbf{x}}_{.2}', \dots, \bar{\mathbf{x}}_{.T}')'$, $\bar{\mathbf{x}}_{.t}' = n^{-1} \sum_{i=1}^{n} \mathbf{x}_{it}'$. This projection matrix uses only explanatory variables to construct observable proxies for the common factors. The corresponding rank condition is

$$\text{rank}(\overline{\boldsymbol{\Gamma}}) = m \leq k, \tag{1.34}$$

where $\overline{\boldsymbol{\Gamma}} = n^{-1} \sum_{i=1}^{n} \boldsymbol{\Gamma}_i$. This type of estimator was already used in the seminal paper by Mundlak (1978) with the difference that only homogeneous factor loadings were considered.

The advantage of this estimator is that the cross-sectional averages of the explanatory variables are exogenous by assumptions contrary to the cross-sectional averages of the dependent variable which are clearly correlated with the error terms at least from the same cross-section even in the case where there is no spatial dependence. As long as the modified rank condition is satisfied, the asymptotic properties of this type of estimator which uses (1.33) are similar to those of $CCEMG$ and $CCEP$ ones. The pooled and mean group CCE estimators, using only explanatory variables to construct proxies for the common factors, are called $CCEPX$ and $CCEMGX$, respectively.

1.2.2.2 Estimating Common Factors Based on Principal Components Analysis

Another way to estimate the common factors is to apply principal component analysis (PCA) to the individuals in the data set. Traditionally, PCA is applied only to the case where the number of panels n is fixed but T is large. Bai (2003) shows that PCA can be applied when n and T are both large. The PCA estimator of the common factors is obtained from the least squares objective function

$$V(m) = \min_{\mathbf{\Gamma},\mathbf{F}} \frac{1}{nT} \sum_{i=1}^{n} \sum_{t=1}^{T} \left(\boldsymbol{\zeta}_{it} - \mathbf{\Gamma}_i'\mathbf{f}_t\right)' \left(\boldsymbol{\zeta}_{it} - \mathbf{\Gamma}_i'\mathbf{f}_t\right), \tag{1.35}$$

subject to the normalization $T^{-1}\mathbf{F}'\mathbf{F} = \mathbf{I}_m$ and the restriction that $\mathbf{\Gamma}'\mathbf{\Gamma}$ is diagonal where $N = nk$, $\mathbf{F} = (\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_T)'$, $\mathbf{\Gamma} = (\mathbf{\Gamma}_1, \mathbf{\Gamma}_2, \ldots, \mathbf{\Gamma}_n)'$ and $\boldsymbol{\zeta}_{it} = (\boldsymbol{\zeta}_{i1t}, \boldsymbol{\zeta}_{i2t}, \ldots, \boldsymbol{\zeta}_{ikt})'$. Then the solution for the estimates of the common factors are given by $\sqrt{T}$ times the first m eigenvectors of the matrix $\sum_{i=1}^{n} \boldsymbol{\zeta}_{i.}\boldsymbol{\zeta}_{i.}'$ with $\boldsymbol{\zeta}_{i.} = (\boldsymbol{\zeta}_{i1}', \boldsymbol{\zeta}_{i2}', \ldots, \boldsymbol{\zeta}_{iT}')'$. Under some weak conditions, Bai (2003) shows that the PCA estimator of the common factors is $\sqrt{n}$ consistent and converges to a normal distribution with a rate of $\min\{T, \sqrt{n}\}$. If $\sqrt{n}/T \to 0$, the convergence rate is found to be $\sqrt{n}$. The assumptions allow for spatial dependence and autocorrelation in the idiosyncratic errors.

Kapetanios and Pesaran (2007) suggest the use of the PCA method to extract the common factors from (1.22). Since both dependent and explanatory variables are expressed as a pure factor model, it is a legitimate method to estimate the common factors. In (1.22) there is information contained on both observed and unobserved common factors, Kapetanios and Pesaran (2007) extract $(m + l)$ principal components prior to slope estimation, with l being the number of observed common factors. An alternative and more efficient way is to run a regression of (1.22) on the observed factors and apply PCA on the residuals to extract m common factors. The resulting estimator of the unit specific slope parameters is given by

$$\widehat{\boldsymbol{\beta}}_{PC,i} = \left(\mathbf{X}_{i.}'\mathbf{M}_p\mathbf{X}_{i.}\right)^{-1}\mathbf{X}_{i.}'\mathbf{M}_p\mathbf{y}_{i.}, \tag{1.36}$$

with

$$\mathbf{M}_p = \mathbf{I}_T - \mathbf{G}(\mathbf{G}'\mathbf{G})^{-}\mathbf{G}', \tag{1.37}$$

where $\mathbf{G} = (\mathbf{D}, \widetilde{\mathbf{F}})$ with $\widetilde{\mathbf{F}}$ being the matrix of observations on the principal components extracted from the matrix $\sum_{i=1}^{n}\widetilde{\mathbf{Z}}_{i.}\widetilde{\mathbf{Z}}_{i.}'$, $\widetilde{\mathbf{Z}}_{i.} = \mathbf{M}_D\mathbf{Z}_i$. where $\mathbf{M}_D = \mathbf{I}_T - \mathbf{D}\left(\mathbf{D}'\mathbf{D}\right)^{-1}\mathbf{D}'$ and $\mathbf{Z}_i. = (\mathbf{z}_{i1}', \mathbf{z}_{i2}', \ldots, \mathbf{z}_{iT}')'$. An MG estimator can be computed from these estimates as in the case of CCE estimators using

$$\widehat{\boldsymbol{\beta}}_{PCMG} = \frac{1}{n}\sum_{i=1}^{n}\widehat{\boldsymbol{\beta}}_{PC,i}, \tag{1.38}$$

and the pooled estimator is defined as

$$\widehat{\boldsymbol{\beta}}_{PCP} = \left(\sum_{i=1}^{n}\mathbf{X}_{i.}'\mathbf{M}_p\mathbf{X}_{i.}\right)^{-1}\sum_{i=1}^{n}\mathbf{X}_{i.}'\mathbf{M}_p\mathbf{y}_{i.}. \tag{1.39}$$

The limiting properties of these estimators are not well known but Kapetanios and Pesaran (2007) provide some finite sample analysis and compare them with CCE estimators. More recently, Greenaway-McGrevy et al. (2012) provide some insight into the asymptotic properties of these estimators under the assumption of homogeneous slope parameters. Their DGP is a restricted version of (1.1) and (1.2) and it is given by

$$y_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\gamma}_i'\mathbf{f}_t + u_{it}, \tag{1.40}$$

$$\mathbf{x}_{it} = \boldsymbol{\Gamma}_i'\mathbf{f}_t + \mathbf{v}_{it}. \tag{1.41}$$

The authors show that in this setting the consistency of principal components estimators depends only on the consistency of the factor estimates performed in the first stage. They also show that the principal components estimator is equivalent to the infeasible estimator which could be computed if the common factors were observable, if $T/n \to 0$ and $n/T^3 \to 0$ as $(n, T) \to \infty$. In this case, the convergence rate of the estimators is $\sqrt{nT}$, since the slope parameters are homogeneous.

Since they are using the factor estimates extracted from both dependent and explanatory variables, the estimators have the disadvantage of providing factor estimates correlated with the error term in the small samples as in the case of CCE estimators. As before, we can apply the PCA on the explanatory variables only to remove the effects of this correlation. These estimators are called $PCPX$ and $PCMGX$ for the case of pooling and MG respectively.

A related but different estimator is proposed by Bai (2009) in a homogeneous slope framework. The model considered corresponds to (1.40) but does not require the explanatory variables to be related to the unobserved common factors as in (1.41). This estimator is the solution to the following non-linear equations

$$\widehat{\boldsymbol{\beta}}_{IPCP} = \left(\sum_{i=1}^{n} \mathbf{X}_{i.}' \mathbf{M}_{\widehat{F}} \mathbf{X}_{i.} \right)^{-1} \sum_{i=1}^{n} \mathbf{X}_{i.}' \mathbf{M}_{\widehat{F}} \mathbf{y}_{i.}, \tag{1.42}$$

$$\left[\frac{1}{nT} \sum_{i=1}^{n} \left(\mathbf{y}_{i.} - \mathbf{X}_{i.} \widehat{\boldsymbol{\beta}}_{IPCP} \right) \left(\mathbf{y}_{i.} - \mathbf{X}_{i.} \widehat{\boldsymbol{\beta}}_{IPCP} \right)' \right] \widehat{\mathbf{F}} = \widehat{\mathbf{F}} \mathbf{V}_{nT}, \tag{1.43}$$

where $\mathbf{M}_{\widehat{F}} = \mathbf{I}_T - \widehat{\mathbf{F}}(\widehat{\mathbf{F}}'\widehat{\mathbf{F}})^{-}\widehat{\mathbf{F}}'$, $\mathbf{V}_{nT}$ is a diagonal matrix containing the m largest eigenvalues of the matrix in the brackets on the left hand side of the equation and $\widehat{\mathbf{F}}$ are the corresponding eigenvectors. To obtain the final estimator of the slope parameters, one can iterate between these two equations until convergence is achieved. Bai (2009) shows that if there is no serial correlation and heteroskedasticity in the error terms, as $n, T \to \infty$ with $T/n \to 0$, we have

$$\sqrt{nT}(\widehat{\boldsymbol{\beta}}_{IPCP} - \boldsymbol{\beta}) \to N(\mathbf{0}, \mathbf{D}_0^{-1}\mathbf{D}_1\mathbf{D}_0^{-1}), \tag{1.44}$$

and if there is no WCD and heteroskedasticity in the error terms, as $n, T \to \infty$ with $n/T \to 0$, we have

$$\sqrt{nT}(\widehat{\boldsymbol{\beta}}_{IPCP} - \boldsymbol{\beta}) \to N(\mathbf{0}, \mathbf{D}_0^{-1}\mathbf{D}_2\mathbf{D}_0^{-1}), \tag{1.45}$$

where $\mathbf{D}_0 = \underset{n,T\to\infty}{\text{plim}} \underline{\mathbf{D}}_0$,

$$\underline{\mathbf{D}}_0 = \frac{1}{nT} \sum_{i=1}^{n} \mathbf{Z}_i^{*\prime} \mathbf{Z}_i^{*},$$

$$\mathbf{D}_1 = \operatorname*{plim}_{n,T\to\infty} \frac{1}{nT} \sum_{i,j=1}^{n} \sigma_{ij} \sum_{t=1}^{T} \mathbf{z}_{it}^{*} \mathbf{z}_{jt}^{*\prime},$$

$$\mathbf{D}_2 = \operatorname*{plim}_{n,T\to\infty} \frac{1}{nT} \sum_{t,s=1}^{T} \omega_{ts} \sum_{i=1}^{n} \mathbf{z}_{it}^{*} \mathbf{z}_{is}^{*\prime},$$

with $\sigma_{ij} = E(u_{it}u_{jt})$, $\omega_{ts} = E(u_{it}u_{is})$ and

$$\mathbf{Z}_i^* = \mathbf{M}_F \mathbf{X}_{i.} - \frac{1}{n} \sum_{k=1}^{n} \mathbf{M}_F \mathbf{X}_{k.} a_{ik}, \tag{1.46}$$

with $a_{ik} = \boldsymbol{\gamma}_i'(\frac{1}{n}\sum_{j=1}^{n} \boldsymbol{\gamma}_j \boldsymbol{\gamma}_j')^{-1}\boldsymbol{\gamma}_k$. This correction in (1.46) is due to the fact that the common factors are unobserved and entered the model non-linearly with their unobserved loadings. If $n, T \to \infty$ with $T/n \to \kappa$, the estimator is asymptotically biased due to the presence of WCD, serially correlated and heteroskedastic error term. In this case, its asymptotic distribution is given by

$$\sqrt{nT}(\widehat{\boldsymbol{\beta}}_{IPCP} - \boldsymbol{\beta}) \to N(\kappa^{1/2}\mathbf{B}_0 + \kappa^{-1/2}\mathbf{C}_0, \mathbf{D}_0^{-1}\mathbf{D}_Z\mathbf{D}_0^{-1}), \tag{1.47}$$

where

$$\mathbf{B}_0 = -\operatorname*{plim}_{n,T\to\infty} \left[\underline{\mathbf{D}}_0^{-1} \frac{1}{n} \sum_{i,j=1}^{n} \frac{(\mathbf{X}_{i.} - \mathbf{V}_i)'\mathbf{F}}{T} \left(\frac{\mathbf{F}'\mathbf{F}}{T}\right)^{-1} \left(\frac{\sum_{k=1}^{n} \boldsymbol{\gamma}_k \boldsymbol{\gamma}_k'}{n}\right)^{-1} \boldsymbol{\gamma}_j \left(\frac{1}{T}\sum_{t=1}^{T} \sigma_{ij,tt}\right) \right], \tag{1.48}$$

$$\mathbf{C}_0 = -\operatorname*{plim}_{n,T\to\infty} \left[\underline{\mathbf{D}}_0^{-1} \frac{1}{nT} \sum_{i=1}^{n} \mathbf{X}_{i.}' \mathbf{M}_F \boldsymbol{\Omega} \mathbf{F} \left(\frac{\mathbf{F}'\mathbf{F}}{T}\right)^{-1} \left(\frac{\sum_{k=1}^{n} \boldsymbol{\gamma}_k \boldsymbol{\gamma}_k'}{n}\right)^{-1} \boldsymbol{\gamma}_i \right], \tag{1.49}$$

$$\mathbf{D}_Z = \operatorname*{plim}_{n,T\to\infty} \frac{1}{nT} \sum_{i,j=1}^{n} \sum_{t,s=1}^{T} \sigma_{ij,ts} \mathbf{z}_{it}^{*} \mathbf{z}_{js}^{*\prime}, \tag{1.50}$$

with $\mathbf{z}_{it}^*$ being the tth row of $\mathbf{Z}_i^*$ and $\boldsymbol{\Omega} = \frac{1}{n}\sum_{k=1}^{n} E\left(\mathbf{u}_{k.}\mathbf{u}_{k.}'\right)$, $\mathbf{V}_i = \frac{1}{n}\sum_{j=1}^{n} a_{ij}\mathbf{X}_{j.}$, $\sigma_{ij,ts} = E\left(u_{it}, u_{js}\right)$. When $\kappa = 0$, $n, T \to \infty$ with $T/n \to 0$ which induces no asymptotic biases. Furthermore, even when $\kappa \neq 0$, if the error terms do not contain WCD and heteroskedasticity $\mathbf{B}_0 = \mathbf{0}$ and if they do not contain serial correlation and heteroskedasticity $\mathbf{C}_0 = \mathbf{0}$.

Song (2013) generalizes the iterative estimation procedure of Bai (2009) to allow for heterogeneity in slope parameters among individuals and lagged dependent variables, shows that $\widehat{\boldsymbol{\beta}}_{IPCP}$ can be replaced in (1.42) and (1.43) by

$$\widehat{\boldsymbol{\beta}}_{IPC,i} = \left(\mathbf{X}_{i.}'\mathbf{M}_{\widehat{F}}\mathbf{X}_{i.}\right)^{-1}\mathbf{X}_{i.}'\mathbf{M}_{\widehat{F}}\mathbf{y}_{i.}, \tag{1.51}$$

and likewise we can iterate over the two non-linear equations until convergence. The author proves that under cross-sectional independence the resulting iterative estimator has the following distribution as $n, T \to \infty$ with $T/n^2 \to 0$

$$\sqrt{T}(\widehat{\boldsymbol{\beta}}_{IPC,i} - \boldsymbol{\beta}_i) \to N(\mathbf{0}, \boldsymbol{\Sigma}_{IPC,i}), \tag{1.52}$$

where $\boldsymbol{\Sigma}_{IPC,i} = \boldsymbol{\Psi}_i^{-1}\boldsymbol{\Xi}_i\boldsymbol{\Psi}_i^{-1}$, and

$$\boldsymbol{\Psi}_i = \operatorname*{plim}_{n,T\to\infty}\frac{1}{T}\mathbf{X}_{i.}'\mathbf{M}_F\mathbf{X}_{i.}, \tag{1.53}$$

$$\boldsymbol{\Xi}_i = \operatorname*{plim}_{n,T\to\infty}\frac{1}{T}\mathbf{X}_{i.}'\mathbf{M}_F E(\mathbf{u}_{i.}\mathbf{u}_{i.}')\mathbf{M}_F\mathbf{X}_{i.}'. \tag{1.54}$$

Song (2013) does not consider the asymptotic distribution of a pooled estimator of the average value of the heterogeneous slopes. However, the author reports numerical and empirical results on the mean group estimator based on the individual estimates which are given by

$$\widehat{\boldsymbol{\beta}}_{IPCMG} = \frac{1}{n}\sum_{i=1}^{n}\widehat{\boldsymbol{\beta}}_{IPC,i}. \tag{1.55}$$

Chudik and Pesaran (2015) conjecture that the asymptotic distribution of (1.55) is

$$\sqrt{n}(\widehat{\boldsymbol{\beta}}_{IPCMG} - \boldsymbol{\beta}) \to N(\mathbf{0}, \boldsymbol{\Omega}_{\delta}), \tag{1.56}$$

with $\boldsymbol{\beta}$ and $\boldsymbol{\Omega}_{\delta}$ as defined above. Their Monte Carlo results and ours confirm the validity of this result.

An alternative way to obtain Bai's (2009) *PC* estimator (1.42) is to iterate between equation (1.43) and

$$\widehat{\boldsymbol{\beta}}_{IPCP} = \left(\sum_{i=1}^{n}\mathbf{X}_{i.}'\mathbf{X}_{i.}\right)^{-1}\sum_{i=1}^{n}\mathbf{X}_{i.}'(\mathbf{y}_{i.} - \widehat{\mathbf{F}}\widehat{\boldsymbol{\gamma}}_i), \tag{1.57}$$

where

$$\widehat{\boldsymbol{\gamma}}_i = T^{-1}\widehat{\mathbf{F}}'(\mathbf{y}_{i.} - \mathbf{X}_{i.}\widehat{\boldsymbol{\beta}}_{IPCP}). \tag{1.58}$$

Bai (2009) finds that this iteration scheme is more robust as it requires the inversion of a single matrix $(\sum_{i=1}^{n} \mathbf{X}_{i.}'\mathbf{X}_{i.})$ rather than an inversion of $(\sum_{i=1}^{n} \mathbf{X}_{i.}'\mathbf{M}_p\mathbf{X}_{i.})$ at every iteration. Similarly, in the case of heterogeneity and instead of using (1.51), individual specific slopes can be estimated by

$$\widehat{\boldsymbol{\beta}}_{IPC,i} = \left(\mathbf{X}_{i.}'\mathbf{X}_{i.}\right)^{-1}\mathbf{X}_{i.}'(\mathbf{y}_{i.} - \widehat{\mathbf{F}}\widehat{\boldsymbol{\gamma}}_i), \tag{1.59}$$

and replacing the estimated slopes accordingly in (1.43) by (1.59). $\widehat{\boldsymbol{\gamma}}_i$ is defined as in (1.58) except that $\widehat{\boldsymbol{\beta}}_{IPCP}$ is replaced by $\widehat{\boldsymbol{\beta}}_{IPC,i}$. These two iteration schemes are used in our Monte Carlo simulations.

The advantage of the iterative PC estimators by Bai (2009) and Song (2013) is that they assume that the factor loadings and the factors are fixed. Therefore, it do not require any constraints on the correlation between the explanatory variables and the common factors. In particular, the data generating process for the explanatory variables is left unrestricted and does not have to be in the form of (1.2). For instance, the explanatory variables can be related to the common factors in a non-linear manner. In this case, the estimators which uses explanatory variables to estimate the common factors, namely CCE-type estimators or non-iterative PC estimators, can fail to estimate the slope parameters consistently. A disadvantage of these estimators is the fact that the number of common factors may not be known in practice. However, it is possible to use information criteria proposed by Bai and Ng (2002) to consistently estimate the number of common factors. Furthermore, Moon and Weidner (2015) show that the consistency of the estimator of Bai (2009) does not require a consistent estimation of the number of factors. In fact, as soon as the number of factors is not underestimated, the resulting estimators are asymptotically equivalent to the estimator based on the true number of common factors.

It is important to note that these iterative estimators by Bai (2009) and Song (2013) are defined by the two non-linear equations (1.42) and (1.43). In practice, they are based on an initial estimation of the slope parameters and stop in h steps after numerical convergence. Originally, Bai (2009) used several initial estimators for the slope parameters, like simple OLS, FE, which ignore the factors structure, and $2WFE$ estimators. Recently, Jiang et al. (2017) show that unless the initial estimator of the slope parameters is consistent, the consistency of these iterative approaches are not guaranteed. In this chapter, the iterative procedures are initialized using the estimators $PCPX$ and $PCMGX$. These estimators are consistent as soon as the explanatory variables have the factor structure given in (1.2).

We have also considered additional estimators based on the PCA methods. Using consistent initialization, as with the estimators $PCPX$ and $PCMGX$, an option is to stop after the first iteration. This estimator is consistent and has the advantage of being computationally less demanding than the iterative estimators. In addition, if the DGP of the dependent variable contains common factors which do not appear in the process generating the explanatory variables, our results show that this procedure produce less bias and more efficient estimates. These estimators are called $PCPX2S$ and $PCMGX2S$.

1.2.2.3 Common Factors and Grouped Patterns of Heterogeneity

The estimators presented in Sections 1.2.2.1 and 1.2.2.2, based on CCE and PCA transformations respectively, assume that each unit has its own factor loadings. Bonhomme and Manresa (2015) assumes simultaneously grouped structures for slope parameters and factor loadings. The objective function is of the form

$$Q_{nT}(\boldsymbol{\beta}^n, \boldsymbol{\gamma}^n) = \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}(y_{it} - \boldsymbol{\beta}_i'\mathbf{x}_{it} - \boldsymbol{\gamma}_i'\mathbf{f}_t)^2, \tag{1.60}$$

with

$$\boldsymbol{\beta}_i = \sum_{g=1}^{K} \boldsymbol{\lambda}_g \mathbb{1}\{i \in G_g\}, \tag{1.61}$$

$$\boldsymbol{\gamma}_i = \sum_{g=1}^{K} \boldsymbol{\phi}_g \mathbb{1}\{i \in G_g\}, \tag{1.62}$$

where K is the number of groups which is assumed here to be known and fixed, $\boldsymbol{\phi}_g$ being the group specific factor loadings, G_g is the set of indexes of n_g units which belong to group g, $\boldsymbol{\gamma}^n = (\boldsymbol{\gamma}_1, \boldsymbol{\gamma}_2, \dots, \boldsymbol{\gamma}_n)$, $\boldsymbol{\phi}^K = (\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \dots, \boldsymbol{\phi}_K)$, $\boldsymbol{\lambda}_g \neq \boldsymbol{\lambda}_{g'}$, $\boldsymbol{\phi}_g \neq \boldsymbol{\phi}_{g'}$, $\forall\ g \neq g'$, $\bigcup\limits_{g=1}^{K} G_g = \{1, 2, \dots, n\}$ and $G_g \cap G_{g'} = \emptyset$, $\forall\ g \neq g'$.

The estimation approach uses an iterative algorithm based on some initial estimates of $\boldsymbol{\beta}^n, \boldsymbol{\gamma}^n$ and iterates until between a group assignment step and the objective function (1.60). The resulting estimator is called grouped fixed effects (GFE). More precisely, the iterative algorithm consists of 4 steps:

Step 1: Select some starting values $\boldsymbol{\lambda}_{(s)}^K$ and $\boldsymbol{\phi}_{(s)}^K$, $s = 0$.

Step 2: Compute for all $i \in \{1, 2, \ldots, n\}$

$$g_i^{(s+1)} = \underset{g \in \{1,2,\ldots,K\}}{\operatorname{argmin}} \sum_{t=1}^{T} (y_{it} - \boldsymbol{\lambda}_g^{(s)\prime} \mathbf{x}_{it} - \boldsymbol{\phi}_g^{(s)\prime} \mathbf{f}_t)^2, \tag{1.63}$$

where g_i is a variable which states the group ith panel unit belongs to.

Step 3: Compute

$$\left(\boldsymbol{\lambda}_{(s+1)}^K, \boldsymbol{\phi}_{(s+1)}^K\right) = \underset{\boldsymbol{\lambda}^n, \boldsymbol{\phi}^n}{\operatorname{argmin}} \sum_{i=1}^{n} \sum_{t=1}^{T} (y_{it} - \boldsymbol{\lambda}_{g_i}^{(s+1)\prime} \mathbf{x}_{it} - \boldsymbol{\phi}_{g_i}^{(s+1)\prime} \mathbf{f}_t)^2. \tag{1.64}$$

Step 4: Go back to step 2 assuming $s = s + 1$. Repeat the process until numerical convergence.

In practice, Bonhomme and Manresa (2015) suggest to select many starting values and choose the final estimate as the one which gives the minimum of the objective function (1.60). They propose also alternative algorithms which are more efficient in certain situations such as a big number of groups such as $K > 10$. In our simulations, we use small values of K. Therefore, the iterative algorithm described above allows to save computing time as highlighted by Bonhomme and Manresa (2015). The authors show that

$$\sqrt{n_g T}(\widehat{\boldsymbol{\lambda}}_g - \boldsymbol{\lambda}_g) \rightarrow N(\mathbf{0}, \mathbf{H}_{2,g}^{-1} \boldsymbol{\Omega}_{2,g} \mathbf{H}_{2,g}^{-1}), \tag{1.65}$$

where

$$\mathbf{H}_{2,g} = \lim_{n_g, T \rightarrow \infty} \frac{1}{n_g T} \sum_{i \in G_g} \sum_{t=1}^{T} E(\widetilde{\mathbf{x}}_{it} \widetilde{\mathbf{x}}_{it}'), \tag{1.66}$$

$$\mathbf{\Omega}_{2,g} = \lim_{n_g,T\to\infty} \frac{1}{n_g T} \sum_{i\in G_g} \sum_{j\in G_g} \sum_{t=1}^{T} \sum_{s=1}^{T} E(u_{it}u_{js}\widetilde{\mathbf{x}}_{it}\widetilde{\mathbf{x}}'_{js}), \tag{1.67}$$

where $\widetilde{\mathbf{x}}_{it} = \mathbf{x}_{it} - \bar{\mathbf{x}}_{gt}$, $\bar{\mathbf{x}}_{gt} = \frac{1}{n_g}\sum_{i\in G_g} \mathbf{x}_{it}$.

The GFE estimator can be seen as an alternative to the estimator of Bai (2009), developed for the case of unit specific factor loadings whereas GFE identifies homogeneity of these loadings within some groups. The IPC estimator is expected to work in a DGP suitable for GFE but GFE should be bias in the case of fully heterogeneous factor loadings. The GFE estimator uses time dummies within groups, therefore, it does not restrict the number of the common factors to be known or even finite. This is not the case for the IPC estimator.

1.2.3 Models with Common Factors and Spatial Effects

In presence of heterogeneous slopes and when the error term contains SCD (common factors) and WCD (spatial effects), Pesaran and Tosetti (2011) show that the non-parametric CCE approach proposed by Pesaran (2006) is still valid and can be used to obtain robust standard errors of the slope coefficients. Consistent estimators for the asymptotic variances of $\widehat{\boldsymbol{\beta}}_{CCEMG}$ and $\widehat{\boldsymbol{\beta}}_{CCEP}$ are given respectively by

$$\widehat{Asy.Var}\left(\widehat{\boldsymbol{\beta}}_{CCEMG}\right) = \frac{1}{n\,(n-1)} \sum_{i=1}^{n} \underline{\widehat{\boldsymbol{\beta}}}_i^* \underline{\widehat{\boldsymbol{\beta}}}_i^{*\prime}, \tag{1.68}$$

and

$$\widehat{Asy.Var}\left(\widehat{\boldsymbol{\beta}}_{CCEP}\right) = \frac{1}{n} \widehat{\mathbf{\Psi}}^{-1} \widehat{\mathbf{\Xi}} \widehat{\mathbf{\Psi}}^{-1}, \tag{1.69}$$

with

$$\widehat{\mathbf{\Psi}} = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{\mathbf{X}'_{i.}\overline{\mathbf{M}}_f \mathbf{X}_{i.}}{T} \right), \tag{1.70}$$

$$\widehat{\mathbf{\Xi}} = \frac{1}{n-1} \sum_{i=1}^{n} \left(\frac{\mathbf{X}'_{i.}\overline{\mathbf{M}}_f \mathbf{X}_{i.}}{T} \right) \underline{\widehat{\boldsymbol{\beta}}}_i^* \underline{\widehat{\boldsymbol{\beta}}}_i^{*\prime} \left(\frac{\mathbf{X}'_{i.}\overline{\mathbf{M}}_f \mathbf{X}_{i.}}{T} \right), \tag{1.71}$$

where $\underline{\widehat{\boldsymbol{\beta}}}_i^* = \widehat{\boldsymbol{\beta}}_{CCE,i} - \widehat{\boldsymbol{\beta}}_{CCEMG}$. The Monte Carlo simulations of Kapetanios et al. (2011) show that a similar approach is valid for PC estimators. In that case, $\overline{\mathbf{M}}_f$ takes the forms associated to the appropriate estimators. For the case of iterative PC estimators, a similar approach is used. The variance estimators proposed by Bai (2009) are valid only for the case of homogeneity and the Monte Carlo simulations of Chudik and Pesaran (2015) show that tests based on these estimators are over-sized when the slopes are heterogeneous. Our results in Section 1.3 show that the robust estimators are correctly sized.

In the case of no unobserved common factors, consistent estimators for the asymptotic variances of $\widehat{\boldsymbol{\beta}}_{MG^*}$ and $\widehat{\boldsymbol{\beta}}_{FE^*}$ are given respectively by

$$\widehat{Asy.Var}\left(\widehat{\boldsymbol{\beta}}_{MG^*}\right) = \frac{1}{n\,(n-1)}\sum_{i=1}^{n}\underline{\widehat{\boldsymbol{\beta}}}_i\underline{\widehat{\boldsymbol{\beta}}}_i', \tag{1.72}$$

and

$$\widehat{Asy.Var}\left(\widehat{\boldsymbol{\beta}}_{FE^*}\right) = \frac{1}{n}\widehat{\mathbf{Q}}^{-1}\widehat{\boldsymbol{\Lambda}}\widehat{\mathbf{Q}}^{-1}, \tag{1.73}$$

with

$$\widehat{\mathbf{Q}} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\mathbf{X}_{i.}'\mathbf{M}_D\mathbf{X}_{i.}}{T}\right), \tag{1.74}$$

$$\widehat{\boldsymbol{\Lambda}} = \frac{1}{n-1}\sum_{i=1}^{n}\left(\frac{\mathbf{X}_{i.}'\mathbf{M}_D\mathbf{X}_{i.}}{T}\right)\underline{\widehat{\boldsymbol{\beta}}}_i\underline{\widehat{\boldsymbol{\beta}}}_i'\left(\frac{\mathbf{X}_{i.}'\mathbf{M}_D\mathbf{X}_{i.}}{T}\right), \tag{1.75}$$

where $\underline{\widehat{\boldsymbol{\beta}}}_i = \widehat{\boldsymbol{\beta}}_i - \widehat{\boldsymbol{\beta}}_{MG^*}$ and $\mathbf{M}_D = \mathbf{I}_T - \mathbf{D}\left(\mathbf{D}'\mathbf{D}\right)^{-1}\mathbf{D}'$ with $\mathbf{D} = (\mathbf{d}_1', \mathbf{d}_2', \ldots, \mathbf{d}_T')'$. In the case of homogeneous slopes, the *CCE* procedure is not applicable. Pesaran and Tosetti (2011) propose a non-parametric variance matrix estimator that adapts the Newey and West (1987)'s heteroskedasticity and autocorrelation consistent (HAC) covariance estimation procedure. More precisely, in the case of no common factors, the authors propose using spatial HAC estimators. The expressions associated to MG^* and FE^* estimators are given respectively by

$$\widehat{Asy.Var}\left(\widehat{\boldsymbol{\beta}}_{MG^*}\right) = \frac{1}{(nT)^2}\sum_{i,j=1}^{n}\sum_{t,s=1}^{T}K\left(\frac{\phi_{ij}}{\phi_n}, \frac{|t-s|}{p+1}\right)\theta_{it}\theta_{js}'\widehat{u}_{it}\widehat{u}_{js}, \tag{1.76}$$

$$\widehat{Asy.Var}\left(\widehat{\boldsymbol{\beta}}_{FE^*}\right) = \widehat{\mathbf{Q}}^{-1}\left[\frac{1}{(nT)^2}\sum_{i,j=1}^{n}\sum_{t,s=1}^{T}K\left(\frac{\phi_{ij}}{\phi_n}, \frac{|t-s|}{p+1}\right)\widetilde{\mathbf{x}}_{it}\widetilde{\mathbf{x}}_{js}'\widehat{u}_{it}\widehat{u}_{js}\right]\widehat{\mathbf{Q}}^{-1}, \tag{1.77}$$

where ϕ_{ij} is the distance between the individuals i and j, ϕ_n is a pre-set function of n, θ_{it} is the tth column of $\boldsymbol{\Theta}_{i.}' = \left(T^{-1}\mathbf{X}_{i.}'\mathbf{M}_D\mathbf{X}_{i.}\right)\mathbf{X}_{i.}'\mathbf{M}_D$, $\widetilde{\mathbf{x}}_{it}$ is the tth column of $\widetilde{\mathbf{X}}_{i.} = \mathbf{X}_{i.}'\mathbf{M}_D$ and $\widehat{u}_{it} = y_{it} - \widehat{\boldsymbol{\alpha}}_i'\mathbf{d}_t + \widehat{\boldsymbol{\beta}}_{(\cdot)}'\mathbf{x}_{it}$ with $\widehat{\boldsymbol{\beta}}_{(\cdot)} = \widehat{\boldsymbol{\beta}}_{MG^*}$ or $\widehat{\boldsymbol{\beta}}_{FE^*}$. As suggested by Bonhomme and

Manresa (2015), when heterogeneity follows a grouped pattern, one can use the estimator defined in (1.77) to estimate the covariance matrix of the GFE estimator. If the interest lies on inference concerning the group specific parameters $\boldsymbol{\lambda}_g$ we can apply this formula to each group in the panel to compute the covariance matrices of the GFE and *C-Lasso* estimators of the group specific parameters.

1.2.4 Forecasting with Heterogeneous Panels with Cross-sectional Dependence

We are interested in post-sample forecasting as defined in Granger and Huang (1997, p. 3). Under the assumptions of RCM in the spirit of Swamy (1970), the predictor $\widehat{y}_{i,T+\tau}$ of $y_{i,T+\tau}$, $\tau = 1, \dots, h$, is given by

$$\widehat{y}_{i,T+\tau} = \widehat{\boldsymbol{\beta}}_i' \mathbf{x}_{i,T+\tau}, \tag{1.78}$$

with

$$\widehat{\boldsymbol{\beta}}_i = \widehat{\boldsymbol{\beta}}_{SW} + \boldsymbol{\Omega}_\delta \mathbf{X}_{i.}' \left(\sigma_i^2 \mathbf{I}_T + \mathbf{X}_{i.} \boldsymbol{\Omega}_\delta \mathbf{X}_{i.}' \right)^{-1} (\mathbf{y}_{i.} - \mathbf{X}_{i.} \widehat{\boldsymbol{\beta}}_{SW}), \tag{1.79}$$

where σ_i^2 and $\boldsymbol{\Omega}_\delta$ are estimated using (1.12) and (1.13), see Lee and Griffiths (1979).

In the context of (1.1) and (1.2), the main problem is that the unobservable common factors $\mathbf{f}_{T+\tau}$ are unknown. Considering possible different unobservable common factors in y_{it} and $\mathbf{x}_{it}$, (1.1) and (1.2) take the form

$$y_{it} = \boldsymbol{\alpha}_i' \mathbf{d}_t + \boldsymbol{\beta}_i' \mathbf{x}_{it} + \boldsymbol{\gamma}_i^{y\prime} \mathbf{f}_t^y + u_{it}, \tag{1.80}$$

$$\mathbf{x}_{it} = \mathbf{A}_i' \mathbf{d}_t + \boldsymbol{\Gamma}_i^{x\prime} \mathbf{f}_t^x + \mathbf{v}_{it}, \tag{1.81}$$

where $\mathbf{f}_t^y$, $\mathbf{f}_t^x$ are the vectors of common factors of sizes $(m_y \times 1)$ and $(m_x \times 1)$. $\boldsymbol{\gamma}_i^{y\prime}$, $\boldsymbol{\Gamma}_i^{x\prime}$ are their respective factor loadings. We define $\mathbf{f}_t$ as the $(m \times 1)$ vector of common factors which contains only once each factor included in $\mathbf{f}_t^y$ and $\mathbf{f}_t^x$. We also define two selection matrices $\mathbf{L}^y$ and $\mathbf{L}^x$ satisfying $\mathbf{L}^y \mathbf{f}_t = \mathbf{f}_t^y$ and $\mathbf{L}^x \mathbf{f}_t = \mathbf{f}_t^x$. If $\operatorname{rank}(\mathbf{L}^y \mathbf{L}^{x\prime}) < m_y$, $\mathbf{f}_t^y$ contains at least one common factor which is not included in $\mathbf{f}_t^x$, therefore, using $\mathbf{x}_{it}$ is not enough to estimate the common factors which should enter in the predictor of the dependent variable. Although in the estimation sample we can use the dependent variable to estimate the common factors in the equation for y_{it}, this is not the case for $T+\tau$ because $y_{i,T+\tau}$ is not observed. To overcome this problem, we assume that some auxiliary variables $\mathbf{w}_{it}$ are observable

$$\mathbf{w}_{it} = \mathbf{A}_i^{w\prime}\mathbf{d}_t + \mathbf{\Gamma}_i^{w\prime}\mathbf{f}_t^w + \boldsymbol{\varsigma}_{it}, \quad t = 1, \ldots, T+h, \tag{1.82}$$

where $\mathbf{w}_{it} = (w_{i1t}, w_{i2t}, \ldots, w_{ik_wt})'$ is a $(k_w \times 1)$ vector of auxiliary observed individual-specific variables, $\mathbf{A}_i^w$ is the $(l \times k_w)$ matrix of factor loadings associated with the observable common factors, $\mathbf{\Gamma}_i^w$ is the $(m_w \times k_w)$ matrix of factor loading associated with the unobservable common factors $\mathbf{f}_t^w$. $\mathbf{L}^w\mathbf{f}_t = \mathbf{f}_t^w$ with rank$(\mathbf{L}^y\mathbf{L}^{w\prime}) = m_y$. $\boldsymbol{\varsigma}_{it}$ is the vector error process. Note that $\mathbf{w}_{it}$ can contain $\mathbf{x}_{it}$ as its components. Then the prediction methodology is based on four steps:

Step 1: Use any estimator which controls for unobserved common factors as described in Section 1.2.2 and compute the residuals

$$\widehat{e}_{it} = y_{it} - \widehat{\boldsymbol{\alpha}}_i'\mathbf{d}_t - \widehat{\boldsymbol{\beta}}_i'\mathbf{x}_{it}, \quad t = 1, \ldots, T. \tag{1.83}$$

In a pooling case, $\widehat{\boldsymbol{\beta}}_i$ should be replaced by the appropriate pooled estimator and

$$\widehat{\boldsymbol{\alpha}}_i = (\mathbf{D}'\mathbf{D})^{-1}\mathbf{D}'(\mathbf{y}_{i.} - \mathbf{X}_{i.}\widehat{\boldsymbol{\beta}}_i). \tag{1.84}$$

Step 2: Use principal components methods in the spirit of Bai (2003), estimate common factors $\mathbf{f}_t^w$ from observed variables $\mathbf{w}_{it}$, $t = 1, \ldots, T+h$, which can include the explanatory variables and some additional variables.

Step 3: Estimate the factor loadings $\widehat{\boldsymbol{\gamma}}_i^w$ from the *OLS* on the regression

$$\widehat{e}_{it} = \boldsymbol{\gamma}_i^w\widehat{\mathbf{f}}_t + \nu_{it}. \tag{1.85}$$

Step 4: Compute the prediction $\widehat{y}_{i,T+\tau}$ using

$$\widehat{y}_{i,T+\tau} = \widehat{\boldsymbol{\alpha}}_i'\mathbf{d}_{T+\tau} + \widehat{\boldsymbol{\beta}}_i'\mathbf{x}_{i,T+\tau} + \widehat{\boldsymbol{\gamma}}_i^{w\prime}\widehat{\mathbf{f}}_{T+\tau}^w. \tag{1.86}$$

1.3 Monte Carlo Study

In this section, we present an extensive Monte Carlo exercise conducted using a general framework which encompasses recent seminal contributions in the literature such as, among others, Pesaran (2006), Bai (2009) and Pesaran and Tosetti (2011).

1.3.1 Design of the Experiments

Our setup generalizes in several directions the framework in Pesaran (2006), Pesaran and Tosetti (2011). The dependent and the explanatory variables are generated by

$$y_{it} = \alpha_{i1} d_{1t} + \beta_{i1} x_{i1t} + \beta_{i2} x_{i2t} + \gamma_{i1} f_{1t} + \gamma_{i2} f_{2t} + u_{it}, \tag{1.87}$$

$$x_{ijt} = a_{ij1} d_{1t} + a_{ij2} d_{2t} + \gamma_{ij1} f_{1t} + \gamma_{ij3} f_{3t} + v_{ijt}, \quad j = 1, 2, \tag{1.88}$$

where $i = 1, 2, \ldots, n$, $t = 1, 2, \ldots, T$, x_{ijt}, $j = 1, 2$, are the observed explanatory variables, d_{jt}, $j = 1, 2$, and f_{jt}, $j = 1, 2, 3$, are the observed and unobserved common factors, respectively, and α_{ij}, β_{ij} and γ_{ijk} are their respective coefficients. The error term of the dependent variable carries spatial dependence and it is generated as a SAR using

$$u_{it} = \rho_i \sum_{j=1}^{n} w_{ij} u_{jt} + \varepsilon_{it}, \quad \text{where} \;\; \varepsilon_{it} \sim N(0, \sigma_i^2), \quad \sigma_i^2 \sim \text{IIDU}(0.5, 1.5), \tag{1.89}$$

where w_{ij} is the element of the spatial weight matrix $\mathbf{W}_n$ in row i and column j. An SMA is also considered as a generating process but the results are similar and they are not reported here. A rook-type spatial weight matrix is used in benchmark setup but we also tried an alternative formulation as in Kelejian and Prucha (1999) which gives a circular structure to the panels. We consider two different cases for ρ_i. These two cases are based on Baltagi and Pirotte (2010), with the main difference being heterogeneity of the parameters in the (first order) SAR (or SMA) models, where $\rho_i = \rho = (0.2, 0.8)$ which corresponds to low and high spatial dependence, respectively. Similarly, we generate the heterogeneous coefficients using

$$\rho_i = \rho + e_i^{\rho}, \quad \text{with} \;\; \rho = \{0.2, 0.8\}, \quad e_i^{\rho} \sim \text{U}(-0.1, 0.1). \tag{1.90}$$

The observed and unobserved common factors are generated as follows

$$d_{1t} = 1, \quad d_{2t} = \rho_d d_{2,t-1} + v_{dt}, \quad v_{dt} \sim N(0, 1-\rho_d^2), \quad \rho_d = 0.5, \quad d_{20} = 0, \tag{1.91}$$

$$f_{jt} = \rho_{fj} f_{j,t-1} + v_{fjt}, \quad v_{fjt} \sim N(0, 1-\rho_{fj}^2), \quad \rho_{fj} = 0.5, \quad f_{j0} = 0, \quad j = 1, 2, 3. \tag{1.92}$$

The disturbances associated to the explanatory variables are generated by a stationary AR(1) process which is given by

$$v_{ijt} = \rho_{v_{ij}} v_{ij,t-1} + \epsilon_{ijt}, \quad \epsilon_{ijt} \sim N(0, 1-\rho_d^2), \quad \rho_{v_{ij}} \sim \text{IIDU}(0.05, 0.95), \tag{1.93}$$

assuming that $v_{ij0} = 0$, $j = 1, 2$. The first 10 observations are discarded to minimize the impact of initial values. The slope coefficients β_{ij} are generated under two different assumptions corresponding to high and low heterogeneity. They are given by

$$\beta_{ij} = \beta_j + \eta_{ij}, \quad \beta_j = 1, \quad \eta_{ij} \sim \text{IID}N(0, \sigma_{\eta_j}^2), \tag{1.94}$$

where $\sigma_{\eta_j}^2 = 0.15$ and $\sigma_{\eta_j}^2 = 0.3$, $j = 1, 2$, correspond to low and high heterogeneity, respectively. These heterogeneity levels in both cases are higher compared to those of Pesaran (2006), Pesaran and Tosetti (2011). The loadings of the observed factors are generated as follows:

$$\alpha_{i1} \sim \text{IID}N(1, 1), \quad (a_{i11}, a_{i21}, a_{i12}, a_{i22})' \sim \text{IID}N(0.5\boldsymbol{\tau}_4, 0.5\mathbf{I}_4), \tag{1.95}$$

where $\boldsymbol{\tau}_4 = (1, 1, 1, 1)'$ and $\boldsymbol{I}_4$, an identity matrix of dimension (4×4). The loadings of the unobserved common factors in the equations for the explanatory variables are generated as

$$\begin{pmatrix} \gamma_{i11} & \gamma_{i13} \\ \gamma_{i21} & \gamma_{i23} \end{pmatrix} \sim \begin{pmatrix} \text{IID}N(0.5, 0.5) & \text{IID}N(0, 0.5) \\ \text{IID}N(0, 0.5) & \text{IID}N(0.5, 0.5) \end{pmatrix}. \tag{1.96}$$

In the perspective of forecasting an additional variable which does not enter into the DGP of the dependent variable, x_{i3t} is generated as

$$x_{i3t} = a_{i31} d_{1t} + a_{i32} d_{2t} + \gamma_{i31} f_{1t} + \gamma_{i33} f_{2t} + v_{i3t}, \tag{1.97}$$

where the factor loadings are given by

$$a_{i31}, a_{i32} \sim \text{IID}N(1.5, 1.02),\ \gamma_{i31}, \gamma_{i32} \sim \text{IID}N(1, 0.1). \tag{1.98}$$

The other terms in (1.97) are defined in the same way as those contained in explanatory variable DGPs (1.88).

Contrary to the case of the factor loadings in the process generating the explanatory variable x_{it}, in this chapter we follow Trapani and Urga (2009) and Phillips and Sul (2003) and draw loadings to generate low and high CD. This is controlled as follows

$$\gamma_{i1}, \gamma_{i2} \sim \begin{cases} \text{IID}N(1, 0.1) \text{ for Low CSD,} \\ \text{IID}N(2, 0.4) \text{ for High CSD.} \end{cases} \tag{1.99}$$

The chosen parameters in (1.99) induce average correlation coefficients among panel units of 0.5 and 0.8, respectively. Four DGPs are considered that distinguish different cases, as summarized in Table 1.1. The constraint parameters reported concern the processes (1.87), (1.88) and (1.90).

Table 1.1: Summary of Experiments Considered

DGPs	Description	Constraints
DGP1	No CSD	$\rho_i = 0$, $\gamma_{i1} = \gamma_{i2} = \gamma_{ij1} = \gamma_{ij3} = 0$
DGP2	Spatial Dependence	$\gamma_{i1} = \gamma_{i2} = \gamma_{ij1} = \gamma_{ij3} = 0$
- Case a	Low Spatial	$\rho = 0.2$
- Case b	High Spatial	$\rho = 0.8$
DGP3	Factor Dependence	$\rho_i = 0$
- Case c	Low Factor Dependence	$\gamma_{i1}, \gamma_{i2} \sim \text{IID}\mathcal{N}(1, 0.1)$
- Case d	High Factor Dependence	$\gamma_{i1}, \gamma_{i2} \sim \text{IID}\mathcal{N}(2, 0.4)$
DGP4	Spatial & Factor Dependence	No constraint
- Case e	Low Spatial & Low Factor Dependence	$\rho = 0.2$, $\gamma_{i1}, \gamma_{i2} \sim \text{IID}\mathcal{N}(1, 0.1)$
- Case f	Low Spatial & High Factor Dependence	$\rho = 0.2$, $\gamma_{i1}, \gamma_{i2} \sim \text{IID}\mathcal{N}(2, 0.4)$
- Case g	High Spatial & Low Factor Dependence	$\rho = 0.8$, $\gamma_{i1}, \gamma_{i2} \sim \text{IID}\mathcal{N}(1, 0.1)$
- Case h	High Spatial & High Factor Dependence	$\rho = 0.8$, $\gamma_{i1}, \gamma_{i2} \sim \text{IID}\mathcal{N}(2, 0.4)$

We evaluate the procedures for $(n, T) = \{20, 50, 100\}$. For each experiment, 2,000 replications are performed. Sixteen estimators are implemented. Nine are heterogeneous estimators (MG^*, SW^*, $CCEMG$, $CCEMGX$, $IPCMG$, $PCMGX$, $PCMGX2S$, *C-Lasso*, GFE) and seven are homogeneous (FE^*, $2WFE$, $CCEP$, $CCEPX$, $IPCP$, $PCPX$, $PCPX2S$). For PC estimators, we assume that the number of unobservable common factors are known. To summarize, the estimators involved in our simulations are:

1. SW^*, MG^*: The estimators follow the same spirit as those defined by (1.7) and (1.14), except that they control for observed common factors;

2. FE^*, $2WFE$: The former corresponds to the fixed effects estimator used by Pesaran and Tosetti (2011) (namely pooled) which controls for observed common factors, whereas the latter is the two-way fixed effects estimator;

3. $CCEMG, CCEP$: They are in (1.26) and (1.29) and are suggested by Pesaran (2006) which use cross-sectional averages of the explanatory variables and the dependent variable to proxy the unobserved common factors;

4. $CCEMGX$, $CCEPX$: The estimators are the same as the two previous ones except that they use the cross-sectional averages of the explanatory variables and an additional exogenous variable to proxy the unobserved common factors;

5. $IPCP$, $IPCMG$: They are in (1.42) and (1.55) except that the iterative procedures are applied to the residuals from a regression of dependent and explanatory variables on observed common factors;

6. $PCMGX$, $PCPX$: The estimators use PCA to extract the unobserved common factors from the only explanatory variables in addition to the factors estimated in the first stage;

7. $PCMGX2S$, $PCPX2S$: They are the two-stage estimators which make use of the factor estimates obtained from the residuals of the $PCMGX$ and $PCPX$ estimators;

8. *C-Lasso*, GFE: The estimators consider that slope parameters are homogeneous within groups but heterogeneous among them. They correspond to Su et al. (2016) using the CCE's transformation (1.24) and Bonhomme and Manresa (2015) estimators, respectively.

The forecasts are computed for the ith individual at future period $T+\tau$, $\tau = 1, \ldots, h$, $h = 10$, and two accuracy measures are used: root mean square error (RMSE) and Theil's U statistic. They are computed as

$$\mathrm{RMSE}_i = \left[\frac{1}{h} \sum_{\tau=1}^{h} \left(\widehat{y}_{i,T+\tau} - y_{i,T+\tau} \right)^2 \right]^{1/2},$$

$$\mathrm{U}_i = \left[\sum_{\tau=1}^{h} \left(\widehat{y}_{i,T+\tau} - y_{i,T+\tau} \right)^2 / \sum_{\tau=1}^{h} y_{i,T+\tau}^2 \right]^{1/2}.$$

To obtain a single average measure, the average of each statistic across units is computed.

1.3.2 Results

The results of the Monte Carlo experiments are discussed in the following subsections. Bias and RMSE results are given in Section 1.3.2.1, size and size adjusted power results are in Section 1.3.2.2 and forecasting accuracy results in Section 1.3.2.3. The comments focus on the most general data generating process, DGP4. Also the most interesting differences between estimation and forecasting methods occur in two cases, Case e and Case g, with SAR errors. These results are given in Appendix 1.A and the discussion focus mainly on these results. Additional results on other DGPs and the results of the robustness checks with SMA errors are given in Appendix A.

1.3.2.1 Bias and RMSE Results

Main results on the homogeneous and heterogeneous estimators are given in Tables 1.2-1.5 whereas Tables 1.6-1.9 report the results on partially heterogeneous estimators. Each table reports bias and RMSE associated to the coefficient β_1 estimates.

Main Results. In all cases, in accordance with the theoretical expectations, MG^*, SW^* and FE^* estimators are inconsistent. The $2WFE$ estimator turns out to be unbiased even if it is based on the assumption of homogeneous factor loadings on the unobserved common factors. This is due to the fact that factor loadings are uncorrelated with the explanatory variables, see Sarafidis and Wansbeek (2012). The remaining estimators are consistent.

Under the assumption of low heterogeneity and low factor dependence, Tables 1.2 and 1.3 consider low and high spatial dependence, respectively. The estimators which control for common factors provide small biases and their RMSEs decline steadily with the increase of n or T. For the $PCMGX$ and $PCPX$ estimators, the bias and RMSE values are higher but they also decline steadily when n or T are getting large. The tendency to have a larger bias characterizes also the $IPCP$ estimator[3] whereas the RMSE values stay in the same bounds as those of the other consistent estimators.

According to Table 1.2, for the $CCEMG$ estimator, two features stand out: as T increases, we obtain 8.26, 6.62 and 6.24 on average whereas as n increases, we obtain 10.04, 6.53 and 4.54, on average. This means that the RMSE decreases at an higher rate when n gets large compared to T. The global average of RMSEs is equal to 7.04 which is the smallest among the estimators considered. However, the RMSE values of $CCEMGX$ and $IPCMG$ are 7.07 and 7.08, respectively, which are not much higher. The bias of $CCEMG$, $CCEMGX$, $PCMG2S$, $2WFE$, $CCEP$, $CCEPX$ and $PCPX2S$ estimators do not look significantly different. When $n = 20$, average RMSE takes large values whatever the estimator considered.

Table 1.3 focuses on high spatial dependence. The main difference concerns RMSE values which are higher for all estimators considered. This is in line with the spatial dependence structure which only affects the disturbances of (1.1). The lowest average RMSE values are associated to the $IPCMG$ estimator which is equal to 7.61. RMSEs of $CCEMG$, $CCEMGX$, $PCMGX2S$ are small too but dominated by those of $CCEP$, $CCEPX$ and $PCPX2S$. This means that the degree of spatial dependence plays an important role in terms of efficiency and does not affect uniformly heterogeneous estimators.

[3]For the $IPCP$ estimator, we also tried to extract three common factors instead of two from the residuals in the iterations. This framework allows to obtain higher size adjusted power values. This is possibly due to the heterogeneity of the slope parameters such that extracting the common factors in the DGP for explanatory variables reduces the variability of the error term. Nevertheless, we report the results obtained using two common factors to be in line with the original literature. Moreover, we applied the bias correction, see (1.47) and (1.48). The results did not improve significantly. Thus, we reported those without bias correction in the tables.

Overall, a general feature that emerges is that the consistent heterogeneous estimators perform better than their homogeneous counterparts and the results are more contrasted when the degree of spatial dependence is high.

In the case of high heterogeneity of the slope coefficients for which the results are reported in Tables 1.4 and 1.5, all consistent heterogeneous estimators are superior to homogeneous ones in all cases except $PCMGX$ and its homogeneous counterpart. Here again, the $IPCMG$ estimator turns out to be a better choice in terms of bias and RMSE.

Tables 1.6 and 1.7 concern with the results of the *C-Lasso* and GFE estimators under low heterogeneity whereas Tables 1.8 and 1.9 report the results for the case of high heterogeneity. The two estimators are time consuming compared to the others. For this reason, we perform for each experiment 1,000 replications instead of 2,000. Two values are used for the number of groups: $K = 2$ and $K = 3$. According to the results, the *C-Lasso* estimator appears strongly biased compared to other robust estimators. In Tables 1.7 and 1.9, which consider high spatial dependence, biases become more reinforced compared to Tables 1.6 and 1.8, irrespective of the degree of heterogeneity. For the GFE estimator, the bias magnitudes are similar to the other heterogeneous and homogeneous estimators. However, in the case of both low and high heterogeneity, bias and RMSE remain higher than those of the $CCEMG$, $CCEMGX$, $PCMGX2S$, $CCEP$, $CCEPX$ and $PCPX2S$.

Additional Findings. Supporting results concerning the level of factor dependence in DGP4 can be seen in Tables A6 and A7 for heterogeneous and homogeneous estimators with low heterogeneity. Their high heterogeneity equivalents are Tables A13 and A14. For the same cases, results on partially heterogeneous estimators are in Tables A20, A21, A27 and A28. The findings above are broadly confirmed in these cases. One important observation is on the lower performance of the $PCMGX$ and $PCPX$ in the case of high factor dependence. Compared to low factor dependence, now these estimators have much higher RMSEs. As they do not control for all common factors in the DGP of the dependent variable, this is an expected result.

The results are confirmed with the other DGPs too. Some interesting findings are discussed in what follows. First, Tables A1 and A8 give the results for the benchmark case of DGP1 for low and high heterogeneity, respectively. In this case all estimators considered are consistent but the estimators which take into account potential unobserved common factors are less efficient than the ones which do not. In smallest sample size, namely when $n, T = 20$, the SW^* estimator has the smallest absolute bias. Its bias is equal to -0.07 in this case. It is also the most efficient heterogeneous estimator: its RMSE is equal to 14.6 when $n, T = 20$ which is considerably lower than the one of MG^* which is 15.84. However, in small samples homogeneous estimators have smaller RMSEs compared to it. As the sample size gets larger it dominates all estimators. Furthermore, in larger samples MG^* is equivalent to this estimator which is in line with the theoretical expectations (Hsiao et al., 1998).

For partially heterogeneous estimators, the results are reported in A15 and A22. The first observation is that the GFE estimator is superior to the *C-Lasso* estimator in terms of bias in all sample sizes. For instance when $n, T = 20$ and $K = 2$, their biases are equal to 0.53 and 2.46, respectively. However, the latter has a smaller RMSE in the case of small n for all values of T. The results are similar when $K = 3$.

The results for DGP2 with SAR errors and low heterogeneity are given in Tables A2 and A3. As there are no unobserved common factors in the DGP, as in the previous case, all estimators considered are consistent in DGP2. In the case of low spatial dependence and low heterogeneity, as before the most efficient estimator is SW^*. Contrary to DGP1, in this case this estimator dominates the pooled estimators in all sample sizes. When $n, T = 20$ its RMSE is equal to 10.95 which is significantly lower than that of MG^* which is 11.23. However, again these two estimators are identical in large samples. When spatial dependence gets higher, the estimator SW^* loses its advantage partially. In this case, both pooling and assuming common factors proves useful for gaining efficiency. As seen in Table A3, all pooled estimators perform better in terms of RMSE compared to their heterogeneous versions in smallest samples ($n, T = 20$). Somewhat surprisingly, $IPCMG$ and $IPCP$ significantly dominate all other estimators. This result shows the advantage of using common factors to deal with spatial dependence, a result which is in line with the findings of Pesaran and Tosetti (2011). Tables A9 and A10 report the results for the same cases with high heterogeneity. The findings are similar. Importantly, the efficiency differences between heterogeneous and pooled estimators are higher in this case, as expected.

The results for the case of SMA errors are given in A43-A44 and A49-A50. The most important observation here is that in this case the estimators which do not control for common factors keep their relative efficiency even in the case of high spatial dependence. The estimator SW^* dominates all other estimators in terms of bias and efficiency.

Tables A16 and A17 concern the partially heterogeneous estimators under low heterogeneity, whereas Tables A23 and A24 report the results for the same cases with high heterogeneity. Once more, GFE estimator is superior to the *C-Lasso* in terms of bias in all sample sizes but the latter provides lower RMSE values. Both estimators are less efficient than the SW^*. The results for the case of SMA errors are given in A55-A56 and A61-A62 and show that these findings are robust to change in the type of spatial process generating the error terms.

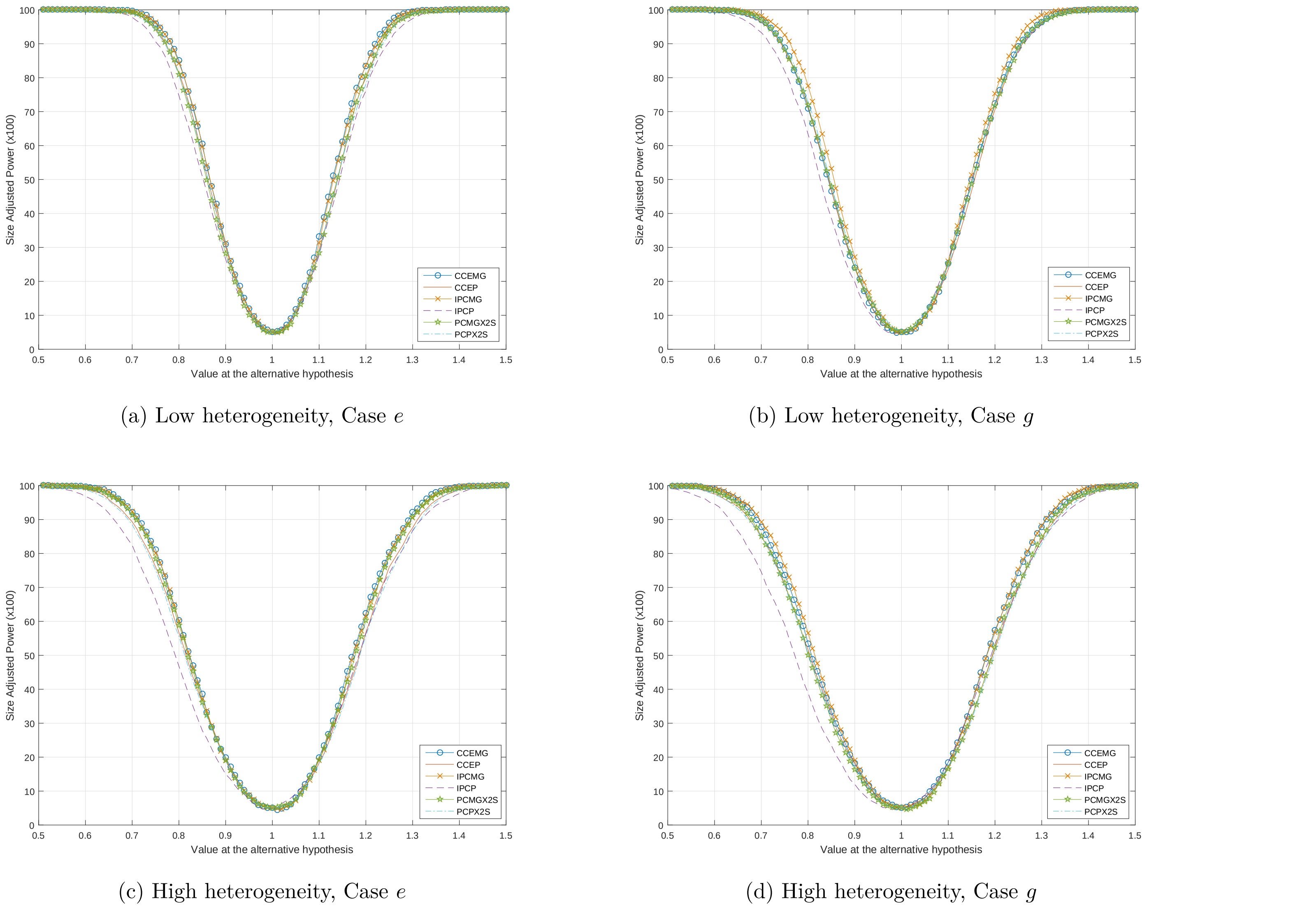
The results for DGP3 with low heterogeneity are given in Tables A4 and A5 whereas Tables A11 and A12 report the results for the same cases with high heterogeneity. The results lead to similar conclusions in the absence of spatial dependence with some exceptions. First of all, once more most of the estimators which are robust to unobserved common factors show good performance in terms of bias and RMSE. In this particular DGP, $CCEMG$ has a superior performance compared to any other estimator in all sample sizes considered. Once more, the estimators $PCMGX$ and $PCPX$ higher bias and RMSE compared to other robust estimators. The results for the partially heterogeneous estimators in the same cases are given in Tables A18, A19, A25 and A26. In this DGP too, *C-Lasso* has a bigger bias compared to GFE. In contrast to other DGPs, it has a higher RMSE in this case. Hence, we can conclude that in the absence of spatial dependence GFE performs better than *C-Lasso* in terms of both bias and RMSE.

1.3.2.2 Size and Size Adjusted Power Results

The size and size adjusted power constitute the second part of the tables mentioned in the previous subsection. The nominal size is set to 5%, the null hypothesis is related to a two-sided test $H_0 : \beta_1 = 1$. The size adjusted power is investigated according to the alternative hypothesis $H_1 : \beta_1 = 0.9$.

Main Results. The empirical size of the tests is very close to the nominal size for all values of n and T for the factor robust estimators except $IPCP$. It can be seen in Tables 1.2-1.5 that, among the consistent estimators, the tests based on the $IPCP$ estimator over-reject the null hypothesis, especially when heterogeneity is high. For the other estimators MG^*, SW^* and FE^*, which are not consistent, their empirical sizes are largely over-sized. Last, the two-sided tests based on C-*Lasso* and GFE estimators are hugely over-sized and their size adjusted power values are very low.

If heterogeneity increases, the size adjusted power decreases regardless of the estimators considered. Figure 1.1 shows that the size adjusted power functions of $CCEMG$, $IPCMG$, $PCMGX2S$, $CCEP$, $IPCP$ and $PCPX2S$. The functions are symmetric, except for $IPCP$, and they have the familiar inverted bell shape. Tests based on all estimators perform well but the $IPCMG$ appears to perform slighty better, closely followed by $CCEMG$. Figure 1.2 sets in parallel the RMSE and size adjusted power of the same estimators considering the alternative hypothesis $H_1 : \beta_1 = 0.7$. When $n = 50$ as T increases, this figure shows that the RMSE values tend to 0 whatever the estimator considered, whereas the size adjusted power values tend to 100. Compared to Tables 1.2-1.5, this figure adds additional information because we also consider $T < 20$. It appears that for $T < 15$, $CCEP$ and $IPCP$ show smaller RMSE values and higher size adjusted power compared to their heterogeneous counterparts $CCEMG$ and $IPCMG$. Nevertheless, as soon as T exceed 15, $CCEMG$ and $IPCMG$ tend to dominate all the other estimators, and especially the homogeneous ones.



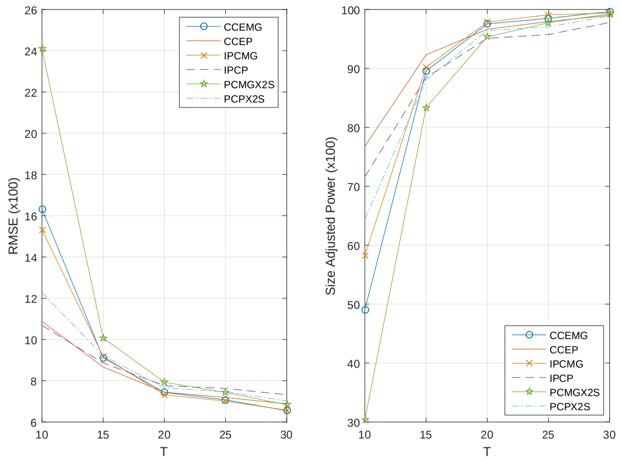
(a) Low heterogeneity, Case e

(b) Low heterogeneity, Case g

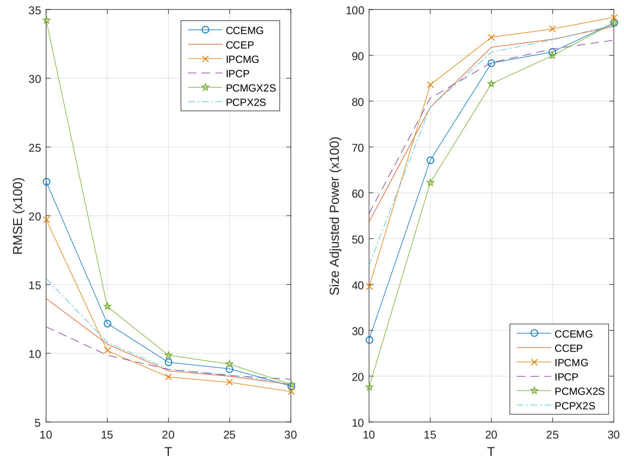
(c) High heterogeneity, Case e

(d) High heterogeneity, Case g

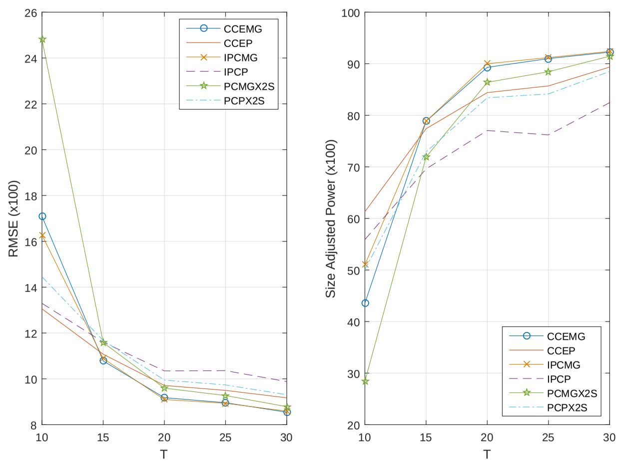
Figure 1.1: Size Adjusted Power Functions of Tests for $(n, T) = (50, 30)$



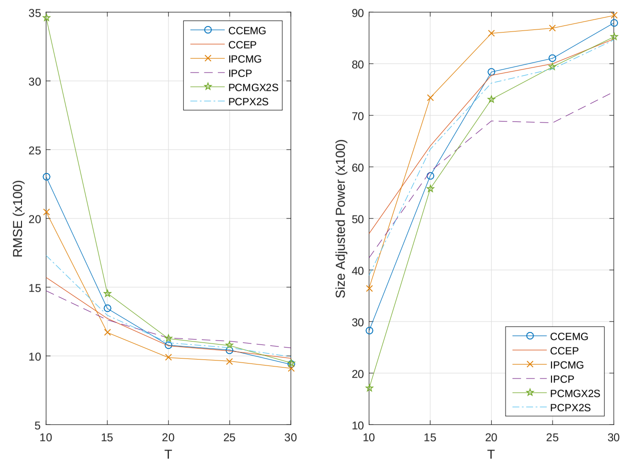
(a) Low heterogeneity, Case e



(b) Low heterogeneity, Case g



(c) High heterogeneity, Case e



(d) High heterogeneity, Case g

Figure 1.2: RMSE and Size Adjusted Power of Various Estimators for $n = 50$

Additional Findings. As in the case of bias and RMSE, additional cases and robustness checks lead to similar conclusions. A few interesting findings are as follows. For DGP1, most of the estimators have size levels close to the nominal value. SW^* shows small size distortions in small samples but as n and T exceed 20, it gets as good as MG^*. The tests based on the $2WFE$ estimator are grossly oversized as expected because its variance estimator is not robust to heterogeneity. Among the estimators which control for unobserved common factors $CCEP$ and $IPCP$ provide tests that are oversized in small samples. In line with the theoretical expectations, SW^* has the highest size adjusted power levels. These are confirmed in DGP2 where there are no unobserved common factors. However, as expected in DGP3, SW^* and MG^* are oversied whereas robust estimators perform well.

1.3.2.3 Forecasting Results

In previous subsections it is seen that *C-Lasso* and GFE results are not satisfactory since the all DGPs assumed individual heterogeneity instead of grouped heterogeneity. Thus, they do not appear in the forecasting tables.

Main Results. The results on the prediction performance of homogeneous and heterogeneous estimators, measured by RMSE and U values for the case of SAR errors are given in Tables 1.10-1.11.

As expected, the estimators which do not take into account CD are performing poorly in terms of RMSE and U values. Moreover, pooling based on these estimators, as in the case of FE^* and $2WFE$, makes the situation generally worse. It can be seen throughout the tables that GLS weighting based on the methods proposed by Swamy (Ind. GLS), provides some improvement in small samples over Ind. OLS. However these differences die out quickly as sample size increases.

In both cases of low and high heterogeneity, predictions using the methods which take into account the heterogeneous slope coefficients are in general the best performers.

In Table 1.10, which reports the results for the case of low heterogeneity, low spatial dependence and low factor dependence, Ind. CCE estimator shows the best prediction ability in very small samples. However, Ind. IPC has lower RMSE and U values as long as T exceeds 20. This is also the case when $T = 100$ even when $n = 20$. Average RMSE over different values of T is found to be 1.198 for Ind. CCE while this value is 1.202 for Ind. IPC. Other estimators which take into account the common factors show reasonable performance. An exception is Ind. PCX which has the poorest forecasting performance among the estimators controlling for common factors. However, its performance gets better in larger samples as Ind. CCE, $CCEX$, IPC and $PCX2S$. Though their performance is generally poorer when compared to their heterogeneous counterparts, in the case of (non-iterative) PC estimators small sample properties of pooled estimators are found to be better. For instance, when n, $T = 20$ the RMSE of Ind. PCX is 1.595 while it is 1.481 for its homogeneous counterpart $PCPX$. This is the case also for Ind. $PCX2S$ and $PCPX2S$.

In Table 1.11, which reports the results for the case of low heterogeneity, high spatial dependence and low factor dependence, Ind. IPC estimator is the preferred method in small samples. However, as time dimension gets larger, the Ind. $PCX2S$ estimator outperforms this estimator. The average RMSE of Ind. $PCX2S$ over different n is 1.731 which is slightly better than Ind. IPC. Among the pooled estimators which control for common factors, as before the $PCPX$ has the poorest performance while all others have very similar predictive ability. In general in this case of high spatial dependence pooled estimators are preferred in small samples, hence, Ind. IPC is an exception.

Similar conclusions can be obtained when we focus on the results for high heterogeneity. For instance, in Table 1.12, the case of high heterogeneity, low spatial dependence and low factor dependence, in addition to the ones mentioned above the main finding is on the relative performance of predictions based on heterogeneous estimators over their homogeneous counterparts. Now the predictions using the estimates of the individual coefficients clearly are better than pooled ones in all cases. One exception is again the RMSE values of Ind. PCX and $PCPX$ estimators for which the difference is smaller. When n, $T = 20$, RMSE for Ind. PCX is found to be 1.595 while it is 1.599 but when the sample size gets larger in either dimension heterogeneous estimation outperforms. The case of high heterogeneity, high spatial dependence and low factor dependence for which the results given in Table 1.13, leads to higher RMSE values of homogeneous and heterogeneous estimators compared to those of Table 1.11.

Additional Findings. Tables A29 and A36 give the results for the benchmark case of DGP1 for low and high heterogeneity, respectively. The SW^* estimator reaches the lowest levels of RMSE and U values in small samples. However, again it is equivalent to the Ind. OLS estimator as T gets larger. In both levels of heterogeneity these estimators perform better than homogeneous estimator FE^*. The estimators which assume unobserved common factors cause deterioration in predictions. Among these, Ind. IPC shows the highest values of RMSE such that when the level of heterogeneity is high its homogeneous counterpart $IPCP$ performs better in small samples. Once again, as sample size gets larger heterogeneous estimator has better properties.

The results for DGP2 with SAR errors and low heterogeneity are given in Tables A30 and A31 whereas Tables A37 and A38 report the results for the same cases with high heterogeneity. The results follow the same pattern as in DGP1 as DGP2 does not have unobserved common factors either. The results for DGP3 are reported in Tables A32, A33,A39 and A40. These results also confirm the previous findings, however, in this case the results are similar to DGP4, as DGP3 contains unobserved common factors.

1.4 Conclusion

In this chapter, we evaluated the performance of alternative homogeneous and heterogeneous panel data estimators. The comparison was performed using several models with cross-sectional dependence modeled by spatial error dependence or common factors or both. These specifications allowed us to compare and contrast the case of WCD (connected to a spatial weighted matrix) with the case of SCD (common factors). We revisited the recent literature on the alternative models and estimation procedures accounting for the nature and the degree of cross sectional dependence, and the size of the time dimension relative to cross-section dimension of the panels. We compare the performance of sixteen estimators using an extensive Monte Carlo exercise using combinations of low and high level of heterogeneity and alternative weak and strong cross-sectional dependence exploring both spatial error dependence and observed and unobserved common factors structures. We also examined the forecasting performance of the estimators and suggested a methodology which makes panel data models with unobserved common factors operational for post-sample prediction.

Our main results can be summarized as follows: (i) Even for small T and n, heterogeneous estimators, especially $CCEMG$ of Pesaran (2006) and $IPCMG$ based on Song's approach, outperforms their homogeneous counterparts, however most of the estimators considered show desirable small sample properties; (ii) The dominance of the heterogeneous estimators are more pronounced for the cases of high heterogeneity, as expected, and this main result holds for different degrees of spatial dependence and factor dependence as well; (iii) The main difference on the performance of the two methods of dealing with unobserved common factors, namely CCE and PC, occurs when we change from low to high spatial dependence whereas changing from low to high factor dependence does not make a big difference in their comparative performance. The estimators based on PC methods are found to be more robust to spatial dependence. This result shows that both methodology work equally good against unobserved factors; (iv) Among the two estimators assuming a grouped structure of heterogeneity, the GFE of Bonhomme and Manresa (2015) performs well in terms of bias and RMSE whereas *C-Lasso* of Su et al. (2016) based on CCE transformation gives less satisfactory results. The performance of GFE improves as we increase the number of groups assumed in the estimation; (v) The findings above are confirmed by the forecasting exercise. Namely, we obtained the lowest values of the traditional measures of forecast accuracy such as MAE, RMSE, Theil's U statistic for heterogeneous estimators.

The main findings in this chapter suggest some interesting further developments. First, in this chapter we assumed that the number of factors is known. If this is not the case, the number should be estimated and investigated from the sample. Second we evaluated the performance of the estimators assuming grouped structure of heterogeneity. It will be interesting to extend our analysis to the case of shrinkage estimators that can be considered as a hybrid solution between homogeneous and heterogeneous estimators (see Maddala et al., 1994, 1997; Hsiao et al., 1998). This is an ongoing research agenda.

Appendices

1.A Tables of Monte Carlo Results

Table 1.2: Low Heterogeneity – DGP4, Case *e*: Low Spatial Dependence & Low Factor Dependence

	Heterogeneous									*Homogeneous*							
	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	17.81	18.18	17.13	17.71	23.49	22.55	20.65	22.23	20	21.38	22.61	21.76	21.92	27.16	27.04	25.59	26.60
50	18.70	17.73	17.36	17.93	22.09	19.68	19.00	20.26	50	22.38	22.52	22.13	22.34	26.03	24.74	23.96	24.91
100	17.92	17.82	17.65	17.80	20.15	19.06	18.62	19.28	100	22.10	22.44	22.60	22.38	24.86	23.87	23.74	24.15
Average	18.14	17.91	17.38	17.81	21.91	20.43	19.42	20.59	Average	21.95	22.52	22.16	22.21	26.01	25.22	24.43	25.22
*SW**									*2WFE*								
20	18.98	18.73	17.42	18.37	24.13	22.88	20.88	22.63	20	-0.25	0.18	-0.17	0.20	12.36	11.75	11.02	11.71
50	19.80	18.36	17.66	18.60	22.85	20.24	19.27	20.78	50	-0.01	-0.25	-0.21	0.16	8.17	7.15	7.02	7.45
100	19.18	18.40	17.99	18.52	21.31	19.60	18.94	19.95	100	-0.05	-0.21	0.09	0.12	5.50	5.09	5.08	5.22
Average	19.32	18.50	17.69	18.50	22.76	20.91	19.70	21.12	Average	0.10	0.21	0.16	0.16	8.68	8.00	7.70	8.13
CCEMG									*CCEP*								
20	-0.31	0.15	-0.20	0.22	11.55	9.59	8.99	10.04	20	-0.50	0.23	-0.19	0.31	12.00	10.25	9.46	10.57
50	0.34	-0.32	0.05	0.23	7.92	5.97	5.71	6.53	50	0.05	-0.22	0.00	0.09	7.76	6.21	5.89	6.62
100	-0.06	-0.18	0.09	0.11	5.30	4.31	4.00	4.54	100	-0.09	-0.25	0.10	0.15	5.38	4.49	4.16	4.68
Average	0.24	0.22	0.11	0.19	8.26	6.62	6.24	7.04	Average	0.22	0.23	0.10	0.18	8.38	6.98	6.50	7.29
CCEMGX									*CCEPX*								
20	-0.25	0.17	-0.20	0.21	11.69	9.63	9.00	10.10	20	-0.52	0.21	-0.18	0.31	12.02	10.25	9.45	10.58
50	0.31	-0.32	0.05	0.23	8.01	5.98	5.72	6.57	50	0.03	-0.22	0.01	0.09	7.79	6.20	5.90	6.63
100	-0.08	-0.19	0.09	0.12	5.31	4.32	4.00	4.54	100	-0.10	-0.25	0.09	0.15	5.38	4.49	4.16	4.68
Average	0.21	0.23	0.11	0.19	8.34	6.64	6.24	7.07	Average	0.22	0.23	0.10	0.18	8.40	6.98	6.50	7.29
IPCMG									*IPCP*								
20	-0.61	0.21	-0.20	0.34	12.42	9.69	9.00	10.37	20	-0.92	-0.50	-0.41	0.61	12.73	11.31	10.44	11.50
50	0.41	-0.26	0.05	0.24	7.82	5.90	5.67	6.46	50	-0.30	-0.58	-0.29	0.39	8.11	6.71	6.61	7.14
100	0.06	-0.16	0.09	0.10	5.06	4.21	3.96	4.41	100	-0.40	-0.45	-0.05	0.30	5.54	5.03	4.78	5.12
Average	0.36	0.21	0.11	0.23	8.43	6.60	6.21	7.08	Average	0.54	0.51	0.25	0.43	8.79	7.68	7.28	7.92
PCMGX									*PCPX*								
20	0.74	0.61	-0.13	0.49	14.78	11.13	9.40	11.77	20	0.49	0.49	-0.19	0.39	13.91	11.19	9.57	11.56
50	0.65	-0.09	0.14	0.29	10.15	6.78	5.99	7.64	50	0.39	-0.04	0.08	0.17	9.22	6.77	6.10	7.36
100	0.42	0.05	0.11	0.19	6.72	4.87	4.24	5.28	100	0.38	-0.04	0.12	0.18	6.40	4.87	4.35	5.20
Average	0.60	0.25	0.12	0.33	10.55	7.59	6.55	8.23	Average	0.42	0.19	0.13	0.25	9.84	7.61	6.67	8.04
PCMGX2S									*PCPX2S*								
20	-0.08	0.35	-0.19	0.21	12.78	9.84	8.94	10.52	20	-0.44	0.21	-0.25	0.30	12.58	10.36	9.26	10.73
50	0.34	-0.25	0.09	0.23	8.64	6.03	5.71	6.79	50	0.00	-0.25	0.00	0.09	8.15	6.25	5.89	6.76
100	-0.01	-0.16	0.11	0.09	5.58	4.32	3.99	4.63	100	-0.07	-0.24	0.11	0.14	5.53	4.52	4.13	4.73
Average	0.14	0.25	0.13	0.17	9.00	6.73	6.21	7.32	Average	0.17	0.23	0.12	0.17	8.75	7.04	6.42	7.41
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	26.30	33.65	33.55	31.17	15.65	17.15	19.30	17.37	20	33.15	40.10	41.30	38.18	14.10	15.25	16.20	15.18
50	48.15	61.05	66.25	58.48	20.50	26.75	34.35	27.20	50	60.00	71.85	74.60	68.82	16.40	23.85	26.35	22.20
100	72.00	85.40	90.55	82.65	30.85	45.90	50.95	42.57	100	80.45	92.15	94.50	89.03	25.80	36.95	40.75	34.50
Average	48.82	60.03	63.45	57.43	22.33	29.93	34.87	29.04	Average	57.87	68.03	70.13	65.34	18.77	25.35	27.77	23.96
*SW**									*2WFE*								
20	30.30	35.45	35.05	33.60	16.05	16.20	18.85	17.03	20	41.50	59.65	70.40	57.18	12.45	12.70	14.05	13.07
50	56.35	64.40	67.50	62.75	21.60	26.90	34.15	27.55	50	39.75	58.55	68.60	55.63	24.05	28.35	28.90	27.10
100	79.95	88.25	91.80	86.67	29.90	47.05	50.50	42.48	100	40.35	59.90	72.15	57.47	43.70	47.20	51.00	47.30
Average	55.53	62.70	64.78	61.01	22.52	30.05	34.50	29.02	Average	40.53	59.37	70.38	56.76	26.73	29.42	31.32	29.16
CCEMG									*CCEP*								
20	6.70	7.60	7.90	7.40	13.35	16.90	17.10	15.78	20	7.25	7.70	8.05	7.67	12.25	16.70	15.80	14.92
50	6.05	6.35	6.40	6.27	22.45	34.70	40.45	32.53	50	5.90	5.95	6.45	6.10	25.00	33.40	38.25	32.22
100	5.00	6.55	4.80	5.45	46.70	60.05	71.15	59.30	100	5.15	6.05	5.50	5.57	45.30	58.65	66.15	56.70
Average	5.92	6.83	6.37	6.37	27.50	37.22	42.90	35.87	Average	6.10	6.57	6.67	6.44	27.52	36.25	40.07	34.61
CCEMGX									*CCEPX*								
20	5.10	6.10	6.95	6.05	13.50	16.05	16.45	15.33	20	5.60	6.65	6.85	6.37	12.50	16.30	15.55	14.78
50	6.05	5.45	5.90	5.80	22.70	35.00	39.75	32.48	50	5.15	5.30	5.95	5.47	25.75	33.05	38.25	32.35
100	4.80	6.55	4.60	5.32	46.50	59.60	71.10	59.07	100	5.00	5.65	5.30	5.32	44.90	57.85	66.60	56.45
Average	5.32	6.03	5.82	5.72	27.57	36.88	42.43	35.63	Average	5.25	5.87	6.03	5.72	27.72	35.73	40.13	34.53
IPCMG									*IPCP*								
20	6.40	6.40	6.75	6.52	11.10	16.30	17.45	14.95	20	8.05	10.05	9.50	9.20	10.25	13.35	14.50	12.70
50	5.75	5.45	5.75	5.65	25.75	35.65	40.80	34.07	50	7.10	6.45	7.70	7.08	23.40	28.15	29.30	26.95
100	5.00	5.70	4.60	5.10	50.65	63.35	72.55	62.18	100	5.80	7.80	6.95	6.85	42.25	45.40	55.20	47.62
Average	5.72	5.85	5.70	5.76	29.17	38.43	43.60	37.07	Average	6.98	8.10	8.05	7.71	25.30	28.97	33.00	29.09
PCMGX									*PCPX*								
20	6.15	6.05	6.20	6.13	11.10	16.25	15.60	14.32	20	5.45	6.05	6.20	5.90	12.10	15.45	16.25	14.60
50	5.35	5.35	5.20	5.30	17.85	27.85	37.70	27.80	50	5.30	4.75	5.05	5.03	18.70	30.10	37.50	28.77
100	5.45	5.65	4.65	5.25	33.30	53.05	66.10	50.82	100	4.90	5.60	5.35	5.28	37.95	49.95	61.85	49.92
Average	5.65	5.68	5.35	5.56	20.75	32.38	39.80	30.98	Average	5.22	5.47	5.53	5.41	22.92	31.83	38.53	31.09
PCMGX2S									*PCPX2S*								
20	5.90	6.35	6.50	6.25	11.00	16.60	17.20	14.93	20	6.80	6.85	7.20	6.95	10.70	16.55	16.10	14.45
50	5.60	5.20	6.20	5.67	21.85	34.55	40.55	32.32	50	5.55	5.40	6.40	5.78	22.70	34.30	36.95	31.32
100	4.95	6.05	4.55	5.18	42.70	59.15	70.70	57.52	100	5.30	5.60	5.25	5.38	43.35	57.35	67.20	55.97
Average	5.48	5.87	5.75	5.70	25.18	36.77	42.82	34.92	Average	5.88	5.95	6.28	6.04	25.58	36.07	40.08	33.91

Table 1.3: Low Heterogeneity – DGP4, Case g: High Spatial Dependence & Low Factor Dependence

	Heterogeneous									*Homogeneous*							
T / N	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	17.75	18.27	17.15	17.72	25.40	23.19	20.86	23.15	20	21.20	22.70	21.79	21.90	28.51	27.54	25.75	27.27
50	18.70	17.66	17.37	17.91	22.92	19.87	19.09	20.63	50	22.45	22.48	22.17	22.37	26.56	24.90	24.08	25.18
100	17.90	17.83	17.64	17.79	20.51	19.19	18.65	19.45	100	22.04	22.45	22.58	22.36	25.06	23.98	23.76	24.27
Average	18.11	17.92	17.38	17.81	22.94	20.75	19.53	21.08	Average	21.90	22.54	22.18	22.21	26.71	25.47	24.53	25.57
*SW**									*2WFE*								
20	19.33	19.23	17.61	18.72	26.18	23.84	21.23	23.75	20	-0.21	0.26	-0.15	0.21	12.91	11.89	11.16	11.99
50	20.24	18.62	17.87	18.91	23.94	20.71	19.55	21.40	50	-0.03	-0.28	-0.22	0.18	8.58	7.33	7.10	7.67
100	19.55	18.66	18.15	18.79	22.02	19.97	19.14	20.38	100	-0.08	-0.19	0.08	0.12	5.89	5.20	5.13	5.41
Average	19.71	18.84	17.88	18.81	24.05	21.51	19.97	21.84	Average	0.11	0.25	0.15	0.17	9.12	8.14	7.79	8.35
CCEMG									*CCEP*								
20	-0.28	0.30	-0.26	0.28	14.24	10.41	9.25	11.30	20	-0.48	0.40	-0.25	0.37	13.65	10.88	9.70	11.41
50	0.33	-0.36	0.02	0.23	10.35	6.61	5.93	7.63	50	0.00	-0.25	-0.03	0.09	9.30	6.73	6.09	7.37
100	0.00	-0.15	0.08	0.08	6.79	4.80	4.19	5.26	100	-0.07	-0.22	0.07	0.12	6.37	4.90	4.34	5.20
Average	0.20	0.27	0.12	0.20	10.46	7.27	6.46	8.06	Average	0.18	0.29	0.12	0.20	9.77	7.50	6.71	7.99
CCEMGX									*CCEPX*								
20	-0.07	0.41	-0.21	0.23	15.23	10.62	9.28	11.71	20	-0.62	0.39	-0.21	0.41	13.72	10.80	9.67	11.39
50	0.30	-0.37	0.01	0.23	10.82	6.67	5.95	7.81	50	-0.01	-0.26	-0.02	0.10	9.26	6.72	6.09	7.36
100	-0.10	-0.18	0.07	0.12	6.88	4.80	4.19	5.29	100	-0.10	-0.23	0.06	0.13	6.35	4.87	4.32	5.18
Average	0.16	0.32	0.10	0.19	10.98	7.36	6.47	8.27	Average	0.25	0.30	0.10	0.21	9.77	7.46	6.69	7.98
IPCMG									*IPCP*								
20	-0.22	0.09	-0.34	0.22	12.48	10.20	9.44	10.70	20	-1.92	-1.51	-1.26	1.56	13.44	11.95	11.04	12.15
50	0.32	-0.19	0.07	0.20	8.90	6.47	6.02	7.13	50	-1.27	-1.45	-1.41	1.38	9.19	7.49	7.20	7.96
100	0.20	-0.02	0.26	0.16	6.01	4.70	4.26	4.99	100	-0.98	-0.92	-0.53	0.81	6.22	5.34	4.93	5.50
Average	0.25	0.10	0.22	0.19	9.13	7.12	6.57	7.61	Average	1.39	1.30	1.06	1.25	9.62	8.26	7.72	8.53
PCMGX									*PCPX*								
20	0.85	0.75	-0.08	0.56	19.59	12.62	9.91	14.04	20	0.44	0.59	-0.18	0.41	17.27	12.38	10.02	13.22
50	0.52	-0.11	0.11	0.25	12.84	7.54	6.26	8.88	50	0.23	-0.08	0.06	0.12	10.98	7.38	6.33	8.23
100	0.38	0.06	0.12	0.18	8.07	5.37	4.44	5.96	100	0.34	-0.03	0.11	0.16	7.26	5.30	4.52	5.69
Average	0.58	0.31	0.10	0.33	13.50	8.51	6.87	9.63	Average	0.34	0.23	0.12	0.23	11.84	8.35	6.96	9.05
PCMGX2S									*PCPX2S*								
20	0.06	0.40	-0.23	0.23	15.30	10.56	9.20	11.69	20	-0.30	0.30	-0.20	0.26	13.88	10.82	9.48	11.40
50	0.48	-0.21	0.06	0.25	11.18	6.62	5.89	7.90	50	-0.11	-0.21	0.00	0.11	9.50	6.71	6.05	7.42
100	0.10	-0.16	0.09	0.12	7.18	4.82	4.17	5.39	100	-0.04	-0.25	0.09	0.12	6.53	4.93	4.31	5.26
Average	0.21	0.26	0.12	0.20	11.22	7.33	6.42	8.32	Average	0.15	0.25	0.09	0.17	9.97	7.49	6.62	8.03
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	22.50	31.70	33.95	29.38	13.20	16.15	17.95	15.77	20	29.35	39.15	40.60	36.37	13.05	15.25	15.90	14.73
50	40.65	56.15	63.35	53.38	18.75	24.95	31.95	25.22	50	55.75	69.70	73.75	66.40	15.40	21.85	26.65	21.30
100	65.05	82.75	89.30	79.03	27.55	42.65	50.45	40.22	100	77.10	90.90	93.90	87.30	21.95	34.95	39.95	32.28
Average	42.73	56.87	62.20	53.93	19.83	27.92	33.45	27.07	Average	54.07	66.58	69.42	63.36	16.80	24.02	27.50	22.77
*SW**									*2WFE*								
20	24.30	35.05	35.55	31.63	12.30	14.75	18.35	15.13	20	32.40	51.80	66.45	50.22	11.45	13.25	13.00	12.57
50	51.50	61.55	66.65	59.90	17.40	25.20	31.85	24.82	50	30.40	50.30	61.05	47.25	22.15	26.75	27.75	25.55
100	74.85	86.30	91.05	84.07	26.35	42.75	51.20	40.10	100	32.00	51.05	63.35	48.80	40.55	45.05	49.75	45.12
Average	50.22	60.97	64.42	58.53	18.68	27.57	33.80	26.68	Average	31.60	51.05	63.62	48.76	24.72	28.35	30.17	27.74
CCEMG									*CCEP*								
20	6.30	7.85	7.80	7.32	11.65	15.05	16.80	14.50	20	6.90	7.00	8.10	7.33	10.80	15.85	16.30	14.32
50	5.75	5.95	6.25	5.98	16.30	28.25	37.75	27.43	50	5.75	5.15	6.10	5.67	18.15	30.10	36.65	28.30
100	5.05	6.60	4.55	5.40	31.25	49.95	67.70	49.63	100	5.25	6.35	5.25	5.62	34.20	48.40	62.10	48.23
Average	5.70	6.80	6.20	6.23	19.73	31.08	40.75	30.52	Average	5.97	6.17	6.48	6.21	21.05	31.45	38.35	30.28
CCEMGX									*CCEPX*								
20	3.05	5.05	5.70	4.60	10.45	14.65	17.20	14.10	20	3.35	5.00	6.10	4.82	10.45	14.95	15.85	13.75
50	4.85	4.70	5.50	5.02	15.10	29.30	37.30	27.23	50	3.70	4.40	4.85	4.32	18.30	28.90	38.00	28.40
100	4.10	6.15	4.30	4.85	31.70	50.50	66.90	49.70	100	4.30	5.85	5.20	5.12	35.00	49.05	61.85	48.63
Average	4.00	5.30	5.17	4.82	19.08	31.48	40.47	30.34	Average	3.78	5.08	5.38	4.75	21.25	30.97	38.57	30.26
IPCMG									*IPCP*								
20	6.55	6.45	6.45	6.48	10.20	15.25	16.40	13.95	20	8.65	7.75	8.40	8.27	9.10	12.60	12.50	11.40
50	6.30	6.00	5.00	5.77	21.10	30.15	38.60	29.95	50	7.35	7.10	6.85	7.10	16.25	20.70	21.45	19.47
100	4.95	6.35	5.05	5.45	41.25	53.55	65.65	53.48	100	6.60	7.50	6.05	6.72	30.85	39.55	49.05	39.82
Average	5.93	6.27	5.50	5.90	24.18	32.98	40.22	32.46	Average	7.53	7.45	7.10	7.36	18.73	24.28	27.67	23.56
PCMGX									*PCPX*								
20	6.10	6.45	6.10	6.22	8.40	12.55	14.95	11.97	20	5.45	6.45	5.95	5.95	8.85	12.85	14.60	12.10
50	5.90	5.45	5.15	5.50	12.25	23.80	35.55	23.87	50	5.90	5.05	5.15	5.37	12.40	25.85	34.20	24.15
100	4.95	5.65	4.85	5.15	26.00	44.80	61.10	43.97	100	4.70	5.75	5.10	5.18	29.60	43.30	59.65	44.18
Average	5.65	5.85	5.37	5.62	15.55	27.05	37.20	26.60	Average	5.35	5.75	5.40	5.50	16.95	27.33	36.15	26.81
PCMGX2S									*PCPX2S*								
20	5.50	7.15	6.90	6.52	10.20	13.70	16.30	13.40	20	5.85	6.45	6.85	6.38	9.50	14.80	15.65	13.32
50	5.00	5.70	5.50	5.40	16.80	29.80	38.85	28.48	50	5.45	5.30	6.00	5.58	17.20	30.30	35.40	27.63
100	5.25	6.35	4.75	5.45	28.90	51.80	66.60	49.10	100	4.85	6.35	5.25	5.48	33.80	48.30	62.85	48.32
Average	5.25	6.40	5.72	5.79	18.63	31.77	40.58	30.33	Average	5.38	6.03	6.03	5.82	20.17	31.13	37.97	29.76

Table 1.4: High Heterogeneity – DGP4, Case *e*: Low Spatial Dependence & Low Factor Dependence

	Heterogeneous									*Homogeneous*							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	17.66	18.17	17.02	17.61	24.78	24.16	22.20	23.71	20	21.15	22.61	21.65	21.80	29.07	29.09	27.56	28.57
50	18.75	17.64	17.36	17.92	22.85	20.27	19.76	20.96	50	22.38	22.48	22.10	22.32	26.97	25.54	24.83	25.78
100	17.88	17.76	17.69	17.78	20.46	19.38	19.05	19.63	100	22.08	22.34	22.65	22.36	25.33	24.24	24.26	24.61
Average	18.09	17.85	17.36	17.77	22.70	21.27	20.34	21.43	Average	21.87	22.48	22.13	22.16	27.12	26.29	25.55	26.32
*SW**									*2WFE*								
20	18.53	18.54	17.20	18.09	25.21	24.37	22.34	23.97	20	-0.37	0.22	-0.26	0.28	16.71	16.14	15.12	15.99
50	19.59	18.08	17.55	18.41	23.38	20.65	19.92	21.32	50	-0.02	-0.31	-0.28	0.20	10.96	9.75	9.64	10.11
100	18.86	18.15	17.91	18.31	21.36	19.74	19.26	20.12	100	-0.06	-0.29	0.14	0.16	7.41	6.97	7.01	7.13
Average	18.99	18.26	17.56	18.27	23.32	21.58	20.51	21.80	Average	0.15	0.27	0.23	0.22	11.69	10.95	10.59	11.08
CCEMG									*CCEP*								
20	-0.46	0.14	-0.31	0.30	14.18	12.93	12.42	13.17	20	-0.67	0.27	-0.29	0.41	15.54	13.96	13.07	14.19
50	0.39	-0.40	0.05	0.28	9.65	8.01	7.91	8.52	50	0.07	-0.27	-0.01	0.11	10.04	8.44	8.18	8.89
100	-0.11	-0.24	0.13	0.16	6.51	5.80	5.55	5.95	100	-0.10	-0.33	0.14	0.19	6.97	6.10	5.80	6.29
Average	0.32	0.26	0.16	0.25	10.11	8.91	8.63	9.22	Average	0.28	0.29	0.15	0.24	10.85	9.50	9.02	9.79
CCEMGX									*CCEPX*								
20	-0.40	0.16	-0.31	0.29	14.29	12.96	12.42	13.22	20	-0.70	0.26	-0.28	0.41	15.57	13.96	13.06	14.20
50	0.36	-0.41	0.06	0.28	9.73	8.02	7.92	8.56	50	0.04	-0.28	0.01	0.11	10.07	8.44	8.19	8.90
100	-0.13	-0.25	0.13	0.17	6.52	5.80	5.55	5.96	100	-0.10	-0.33	0.14	0.19	6.97	6.10	5.80	6.29
Average	0.30	0.27	0.16	0.25	10.18	8.93	8.63	9.25	Average	0.28	0.29	0.14	0.24	10.87	9.50	9.01	9.79
IPCMG									*IPCP*								
20	-0.76	0.19	-0.31	0.42	14.92	13.03	12.43	13.46	20	-1.82	-1.40	-1.26	1.49	16.80	15.50	14.59	15.63
50	0.47	-0.35	0.05	0.29	9.56	7.97	7.87	8.47	50	-1.05	-1.63	-1.41	1.37	10.62	9.30	9.22	9.71
100	0.02	-0.22	0.13	0.12	6.32	5.72	5.53	5.85	100	-1.29	-1.56	-1.17	1.34	7.50	6.97	6.60	7.03
Average	0.42	0.26	0.17	0.28	10.27	8.90	8.61	9.26	Average	1.39	1.53	1.28	1.40	11.64	10.59	10.14	10.79
PCMGX									*PCPX*								
20	0.58	0.60	-0.24	0.47	16.86	14.16	12.68	14.57	20	0.36	0.51	-0.30	0.39	16.85	14.64	12.98	14.82
50	0.71	-0.17	0.14	0.34	11.52	8.61	8.11	9.41	50	0.39	-0.10	0.07	0.19	11.24	8.84	8.30	9.46
100	0.38	-0.02	0.15	0.18	7.73	6.22	5.73	6.56	100	0.37	-0.11	0.17	0.22	7.77	6.37	5.92	6.69
Average	0.56	0.26	0.18	0.33	12.04	9.66	8.84	10.18	Average	0.38	0.24	0.18	0.27	11.95	9.95	9.07	10.32
PCMGX2S									*PCPX2S*								
20	-0.23	0.33	-0.30	0.29	15.15	13.14	12.37	13.55	20	-0.47	0.17	-0.38	0.34	16.00	14.13	12.95	14.36
50	0.39	-0.34	0.09	0.27	10.25	8.06	7.90	8.74	50	0.03	-0.29	-0.02	0.11	10.43	8.50	8.20	9.04
100	-0.05	-0.23	0.15	0.14	6.75	5.80	5.54	6.03	100	-0.07	-0.31	0.15	0.18	7.14	6.11	5.76	6.34
Average	0.22	0.30	0.18	0.23	10.72	9.00	8.60	9.44	Average	0.19	0.26	0.18	0.21	11.19	9.58	8.97	9.91
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	20.65	25.20	22.80	22.88	14.50	13.55	16.45	14.83	20	24.35	28.50	28.70	27.18	11.20	13.00	13.55	12.58
50	40.50	45.20	49.20	44.97	18.40	21.15	26.40	21.98	50	47.25	54.90	55.60	52.58	15.45	20.05	19.35	18.28
100	62.00	71.95	75.00	69.65	26.00	37.05	38.60	33.88	100	68.00	78.65	81.00	75.88	22.50	30.00	29.50	27.33
Average	41.05	47.45	49.00	45.83	19.63	23.92	27.15	23.57	Average	46.53	54.02	55.10	51.88	16.38	21.02	20.80	19.40
*SW**									*2WFE*								
20	22.60	25.60	23.75	23.98	13.75	13.95	15.70	14.47	20	48.15	65.45	74.35	62.65	9.05	9.70	9.15	9.30
50	45.05	47.55	49.85	47.48	18.55	22.45	26.25	22.42	50	47.20	63.75	72.80	61.25	14.05	17.35	17.20	16.20
100	66.95	74.30	75.65	72.30	24.95	36.50	39.15	33.53	100	47.15	65.65	76.15	62.98	27.55	28.85	31.50	29.30
Average	44.87	49.15	49.75	47.92	19.08	24.30	27.03	23.47	Average	47.50	64.95	74.43	62.29	16.88	18.63	19.28	18.27
CCEMG									*CCEP*								
20	6.65	7.80	8.25	7.57	10.90	11.10	10.35	10.78	20	7.80	7.70	8.25	7.92	9.95	10.90	10.35	10.40
50	6.20	5.90	6.60	6.23	16.45	21.65	22.20	20.10	50	6.05	5.75	6.45	6.08	17.05	20.70	21.60	19.78
100	5.10	6.30	4.85	5.42	32.80	36.90	44.05	37.92	100	5.10	5.80	5.60	5.50	29.25	34.20	40.55	34.67
Average	5.98	6.67	6.57	6.41	20.05	23.22	25.53	22.93	Average	6.32	6.42	6.77	6.50	18.75	21.93	24.17	21.62
CCEMGX									*CCEPX*								
20	5.25	6.65	7.10	6.33	10.55	10.55	10.55	10.55	20	5.85	6.70	6.80	6.45	9.55	10.30	10.20	10.02
50	5.90	5.20	6.05	5.72	16.85	21.50	22.25	20.20	50	5.55	5.20	6.00	5.58	17.75	20.05	21.55	19.78
100	4.95	6.10	4.65	5.23	31.90	35.75	44.45	37.37	100	5.00	5.30	5.20	5.17	29.25	34.35	40.55	34.72
Average	5.37	5.98	5.93	5.76	19.77	22.60	25.75	22.71	Average	5.47	5.73	6.00	5.73	18.85	21.57	24.10	21.51
IPCMG									*IPCP*								
20	5.90	6.45	7.00	6.45	8.85	10.55	10.85	10.08	20	9.35	11.55	11.25	10.72	8.15	9.10	9.30	8.85
50	5.70	5.40	5.65	5.58	16.80	21.80	22.45	20.35	50	7.60	8.00	8.60	8.07	14.65	15.65	13.95	14.75
100	4.95	5.75	4.80	5.17	35.40	39.10	44.20	39.57	100	7.00	8.70	8.30	8.00	21.00	20.20	23.65	21.62
Average	5.52	5.87	5.82	5.73	20.35	23.82	25.83	23.33	Average	7.98	9.42	9.38	8.93	14.60	14.98	15.63	15.07
PCMGX									*PCPX*								
20	5.80	6.50	6.35	6.22	9.60	11.15	9.80	10.18	20	5.90	6.25	6.45	6.20	9.25	11.60	10.55	10.47
50	5.30	5.30	5.25	5.28	14.70	19.60	23.85	19.38	50	5.50	4.20	5.25	4.98	14.60	19.55	22.30	18.82
100	5.45	5.35	5.00	5.27	26.65	35.15	40.60	34.13	100	5.00	5.50	5.50	5.33	26.55	32.05	36.95	31.85
Average	5.52	5.72	5.53	5.59	16.98	21.97	24.75	21.23	Average	5.47	5.32	5.73	5.51	16.80	21.07	23.27	20.38
PCMGX2S									*PCPX2S*								
20	5.50	6.55	6.75	6.27	9.55	11.65	10.95	10.72	20	7.25	7.75	7.95	7.65	9.20	10.95	9.80	9.98
50	5.90	4.95	6.15	5.67	16.05	22.30	23.55	20.63	50	6.05	5.35	6.50	5.97	16.10	21.55	20.70	19.45
100	5.05	5.85	4.45	5.12	31.10	36.70	44.65	37.48	100	5.40	5.50	5.50	5.47	27.35	34.65	39.75	33.92
Average	5.48	5.78	5.78	5.68	18.90	23.55	26.38	22.94	Average	6.23	6.20	6.65	6.36	17.55	22.38	23.42	21.12

Table 1.5: High Heterogeneity – DGP4, Case g: High Spatial Dependence & Low Factor Dependence

	Heterogeneous									*Homogeneous*							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	17.59	18.26	17.04	17.63	26.60	24.76	22.39	24.59	20	20.97	22.71	21.67	21.78	30.37	29.57	27.71	29.22
50	18.75	17.57	17.38	17.90	23.64	20.46	19.83	21.31	50	22.45	22.44	22.14	22.34	27.47	25.71	24.94	26.04
100	17.85	17.76	17.68	17.76	20.82	19.51	19.09	19.81	100	22.03	22.35	22.63	22.34	25.53	24.34	24.28	24.72
Average	18.07	17.86	17.36	17.76	23.69	21.58	20.44	21.90	Average	21.82	22.50	22.15	22.16	27.79	26.54	25.64	26.66
*SW**									*2WFE*								
20	18.92	18.94	17.34	18.40	27.24	25.18	22.62	25.01	20	-0.33	0.30	-0.24	0.29	17.10	16.24	15.23	16.19
50	19.98	18.26	17.70	18.65	24.39	21.04	20.12	21.85	50	-0.04	-0.35	-0.30	0.23	11.24	9.88	9.69	10.27
100	19.19	18.34	18.02	18.52	22.02	20.04	19.41	20.49	100	-0.09	-0.27	0.13	0.16	7.71	7.06	7.04	7.27
Average	19.36	18.51	17.68	18.52	24.55	22.09	20.72	22.45	Average	0.15	0.31	0.22	0.23	12.02	11.06	10.65	11.24
CCEMG									*CCEP*								
20	-0.42	0.29	-0.37	0.36	16.41	13.54	12.60	14.18	20	-0.65	0.44	-0.35	0.48	16.77	14.41	13.26	14.82
50	0.38	-0.44	0.02	0.28	11.71	8.48	8.04	9.41	50	0.01	-0.30	-0.04	0.12	11.29	8.84	8.30	9.48
100	-0.04	-0.22	0.12	0.13	7.77	6.19	5.69	6.55	100	-0.08	-0.30	0.12	0.17	7.75	6.42	5.93	6.70
Average	0.28	0.31	0.17	0.26	11.96	9.40	8.78	10.05	Average	0.24	0.35	0.17	0.25	11.93	9.89	9.16	10.33
CCEMGX									*CCEPX*								
20	-0.23	0.40	-0.32	0.31	17.27	13.70	12.62	14.53	20	-0.80	0.44	-0.31	0.52	16.85	14.34	13.21	14.80
50	0.35	-0.46	0.02	0.28	12.15	8.54	8.06	9.58	50	0.00	-0.32	-0.03	0.12	11.25	8.83	8.30	9.46
100	-0.14	-0.24	0.11	0.17	7.86	6.18	5.69	6.58	100	-0.10	-0.32	0.11	0.18	7.73	6.40	5.91	6.68
Average	0.24	0.37	0.15	0.25	12.43	9.47	8.79	10.23	Average	0.30	0.36	0.15	0.27	11.95	9.86	9.14	10.31
IPCMG									*IPCP*								
20	-0.37	0.07	-0.45	0.30	14.92	13.41	12.77	13.70	20	-2.57	-2.27	-1.70	2.18	17.48	16.08	14.96	16.17
50	0.37	-0.28	0.08	0.24	10.48	8.40	8.11	9.00	50	-2.03	-2.17	-2.15	2.11	11.82	9.97	9.69	10.49
100	0.16	-0.09	0.30	0.18	7.10	6.11	5.75	6.32	100	-1.70	-1.82	-1.38	1.63	8.16	7.24	6.77	7.39
Average	0.30	0.15	0.27	0.24	10.83	9.31	8.87	9.67	Average	2.10	2.09	1.74	1.98	12.49	11.10	10.48	11.35
PCMGX									*PCPX*								
20	0.70	0.74	-0.19	0.54	21.15	15.35	13.05	16.52	20	0.31	0.61	-0.28	0.40	19.64	15.53	13.31	16.16
50	0.57	-0.20	0.12	0.29	13.94	9.22	8.28	10.48	50	0.23	-0.15	0.05	0.15	12.74	9.32	8.45	10.17
100	0.34	-0.01	0.16	0.17	8.93	6.64	5.87	7.15	100	0.34	-0.10	0.16	0.20	8.48	6.71	6.04	7.08
Average	0.53	0.31	0.16	0.33	14.68	10.40	9.07	11.38	Average	0.29	0.29	0.16	0.25	13.62	10.52	9.27	11.14
PCMGX2S									*PCPX2S*								
20	-0.09	0.39	-0.34	0.27	17.31	13.69	12.56	14.52	20	-0.36	0.28	-0.30	0.31	17.00	14.50	13.06	14.85
50	0.53	-0.30	0.06	0.30	12.46	8.50	8.02	9.66	50	-0.08	-0.30	-0.02	0.13	11.58	8.90	8.31	9.60
100	0.06	-0.22	0.13	0.14	8.14	6.20	5.67	6.67	100	-0.06	-0.30	0.13	0.16	7.93	6.47	5.89	6.77
Average	0.22	0.30	0.18	0.23	12.64	9.47	8.75	10.28	Average	0.17	0.29	0.15	0.20	12.17	9.96	9.09	10.41
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	18.65	24.10	22.35	21.70	11.40	13.30	15.20	13.30	20	23.25	28.20	28.85	26.77	11.25	12.80	13.45	12.50
50	35.45	42.60	48.10	42.05	15.65	22.00	25.45	21.03	50	44.95	52.55	54.35	50.62	14.15	18.85	20.75	17.92
100	55.55	69.85	73.50	66.30	23.80	34.25	38.20	32.08	100	65.55	77.15	80.35	74.35	19.85	29.90	29.75	26.50
Average	36.55	45.52	47.98	43.35	16.95	23.18	26.28	22.14	Average	44.58	52.63	54.52	50.58	15.08	20.52	21.32	18.97
*SW**									*2WFE*								
20	21.85	25.35	23.65	23.62	12.35	13.95	15.20	13.83	20	40.85	59.85	71.65	57.45	9.00	9.60	9.05	9.22
50	42.75	45.70	49.65	46.03	16.65	22.65	25.25	21.52	50	38.95	57.80	68.15	54.97	14.70	17.15	17.10	16.32
100	64.25	72.75	74.70	70.57	21.35	34.90	38.75	31.67	100	40.15	59.95	70.45	56.85	26.00	26.60	30.40	27.67
Average	42.95	47.93	49.33	46.74	16.78	23.83	26.40	22.34	Average	39.98	59.20	70.08	56.42	16.57	17.78	18.85	17.73
CCEMG									*CCEP*								
20	6.40	7.70	7.85	7.32	8.95	10.45	11.15	10.18	20	7.25	7.75	7.95	7.65	8.80	10.20	10.35	9.78
50	5.60	5.85	6.35	5.93	14.00	18.60	22.80	18.47	50	5.45	5.30	6.25	5.67	14.50	19.30	20.75	18.18
100	5.35	6.55	4.85	5.58	23.30	30.85	42.95	32.37	100	5.20	6.25	5.40	5.62	24.80	30.20	38.75	31.25
Average	5.78	6.70	6.35	6.28	15.42	19.97	25.63	20.34	Average	5.97	6.43	6.53	6.31	16.03	19.90	23.28	19.74
CCEMGX									*CCEPX*								
20	3.80	5.85	6.15	5.27	9.75	10.40	11.15	10.43	20	3.90	6.15	6.25	5.43	8.95	10.05	10.80	9.93
50	5.30	4.70	5.55	5.18	12.35	20.15	22.25	18.25	50	4.10	4.65	5.55	4.77	14.55	18.95	21.25	18.25
100	4.50	6.30	4.80	5.20	24.65	31.00	42.25	32.63	100	4.40	5.80	5.10	5.10	24.85	29.90	38.10	30.95
Average	4.53	5.62	5.50	5.22	15.58	20.52	25.22	20.44	Average	4.13	5.53	5.63	5.10	16.12	19.63	23.38	19.71
IPCMG									*IPCP*								
20	6.00	6.95	7.15	6.70	9.35	9.95	10.60	9.97	20	9.70	9.05	10.60	9.78	6.55	8.55	8.10	7.73
50	5.60	5.25	5.35	5.40	17.40	20.50	23.35	20.42	50	8.00	8.35	8.45	8.27	11.45	11.65	12.80	11.97
100	5.15	6.35	5.05	5.52	30.50	33.95	42.20	35.55	100	7.80	8.55	8.45	8.27	18.10	17.25	22.90	19.42
Average	5.58	6.18	5.85	5.87	19.08	21.47	25.38	21.98	Average	8.50	8.65	9.17	8.77	12.03	12.48	14.60	13.04
PCMGX									*PCPX*								
20	6.05	6.90	6.00	6.32	7.15	9.60	11.05	9.27	20	5.85	6.65	5.95	6.15	8.00	10.30	10.85	9.72
50	5.55	5.40	5.20	5.38	10.90	16.90	21.85	16.55	50	5.80	4.70	5.15	5.22	11.35	18.50	21.25	17.03
100	5.10	5.90	4.95	5.32	21.35	31.25	39.30	30.63	100	5.10	5.55	5.50	5.38	21.50	28.05	36.80	28.78
Average	5.57	6.07	5.38	5.67	13.13	19.25	24.07	18.82	Average	5.58	5.63	5.53	5.58	13.62	18.95	22.97	18.51
PCMGX2S									*PCPX2S*								
20	5.55	7.05	7.00	6.53	8.90	9.40	11.05	9.78	20	6.25	7.00	7.35	6.87	8.25	10.70	10.85	9.93
50	5.45	5.20	6.00	5.55	14.15	19.90	22.05	18.70	50	6.05	5.30	6.00	5.78	13.10	19.55	20.80	17.82
100	5.30	6.50	4.65	5.48	22.90	32.35	42.55	32.60	100	5.45	6.20	5.15	5.60	22.95	29.45	39.35	30.58
Average	5.43	6.25	5.88	5.86	15.32	20.55	25.22	20.36	Average	5.92	6.17	6.17	6.08	14.77	19.90	23.67	19.44

Table 1.6: Partially Heterogeneous Estimators – Low Heterogeneity – DGP4, Case e: Low Spatial Dependence & Low Factor Dependence

	$K=2$								$K=3$							
T	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.15	0.31	-0.16	0.21	12.33	10.68	10.18	11.06	0.11	0.55	-0.11	0.26	12.18	10.34	10.00	10.84
50	-0.28	-0.10	-0.38	0.25	7.27	6.72	6.64	6.88	-0.19	-0.19	-0.39	0.26	7.19	6.59	6.29	6.69
100	0.20	-0.17	-0.27	0.21	5.44	4.76	4.75	4.98	0.10	-0.11	-0.24	0.15	5.34	4.63	4.64	4.87
Average	0.21	0.19	0.27	0.23	8.35	7.39	7.19	7.64	0.13	0.28	0.25	0.22	8.24	7.19	6.97	7.47
C-Lasso CCE																
20	1.62	2.27	1.71	1.87	11.17	10.45	10.05	10.55	2.16	3.01	2.53	2.57	11.24	10.69	10.26	10.73
50	1.84	2.03	1.75	1.88	7.27	6.89	6.41	6.86	2.90	3.05	2.68	2.88	7.52	7.22	6.80	7.18
100	2.15	1.45	1.74	1.78	5.88	4.91	4.78	5.19	3.10	2.70	2.70	2.83	6.04	5.28	5.08	5.47
Average	1.87	1.92	1.74	1.84	8.11	7.41	7.08	7.53	2.72	2.92	2.64	2.76	8.27	7.73	7.38	7.79
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	30.50	33.60	38.60	34.23	11.40	10.70	9.60	10.57	38.40	40.80	44.10	41.10	9.00	10.10	9.70	9.60
50	22.50	29.40	33.50	28.47	22.40	20.10	19.20	20.57	27.40	32.40	38.10	32.63	18.00	18.10	15.00	17.03
100	21.20	29.80	30.80	27.27	37.00	36.60	36.90	36.83	25.40	33.00	34.10	30.83	33.40	29.50	36.80	33.23
Average	24.73	30.93	34.30	29.99	23.60	22.47	21.90	22.66	30.40	35.40	38.77	34.86	20.13	19.23	20.50	19.96
C-Lasso CCE																
20	18.80	20.80	21.50	20.37	11.50	12.30	13.70	12.50	31.40	34.10	38.70	34.73	11.00	11.20	9.40	10.53
50	13.20	13.20	12.90	13.10	22.80	28.40	25.10	25.43	22.60	27.20	27.30	25.70	16.60	18.20	17.40	17.40
100	12.60	11.50	13.30	12.47	36.20	38.80	35.00	36.67	23.50	24.50	25.20	24.40	31.00	28.70	26.50	28.73
Average	14.87	15.17	15.90	15.31	23.50	26.50	24.60	24.87	25.83	28.60	30.40	28.28	19.53	19.37	17.77	18.89

Table 1.7: Partially Heterogeneous Estimators – Low Heterogeneity – DGP4, Case g: High Spatial Dependence & Low Factor Dependence

	$K=2$								$K=3$							
T	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.72	0.23	-0.15	0.36	13.40	11.34	10.79	11.84	0.39	0.36	-0.24	0.33	13.36	11.44	10.51	11.77
50	-0.39	-0.21	-0.48	0.36	7.90	6.95	6.81	7.22	-0.24	-0.31	-0.33	0.30	7.79	6.77	6.52	7.03
100	0.18	-0.20	-0.29	0.23	5.86	4.90	4.86	5.20	0.12	-0.18	-0.32	0.21	5.73	4.76	4.74	5.08
Average	0.43	0.21	0.31	0.32	9.05	7.73	7.49	8.09	0.25	0.29	0.30	0.28	8.96	7.66	7.26	7.96
C-Lasso CCE																
20	2.33	2.14	0.60	1.69	13.29	10.75	9.82	11.29	2.04	2.96	1.59	2.20	13.36	10.86	9.97	11.40
50	2.20	1.58	1.38	1.72	8.23	6.98	6.54	7.25	2.92	2.68	2.43	2.68	8.17	7.26	6.72	7.39
100	2.58	1.54	1.40	1.84	6.77	5.36	4.93	5.68	3.20	2.80	2.53	2.84	6.76	5.57	5.32	5.88
Average	2.37	1.76	1.13	1.75	9.43	7.70	7.10	8.07	2.72	2.81	2.18	2.57	9.43	7.90	7.34	8.22
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	28.20	29.10	32.50	29.93	9.40	12.90	10.90	11.07	33.60	36.20	36.40	35.40	10.70	11.40	8.80	10.30
50	18.80	25.50	29.00	24.43	19.00	20.20	23.90	21.03	20.30	26.40	28.80	25.17	20.60	24.10	18.80	21.17
100	16.00	25.30	27.60	22.97	37.00	37.30	39.40	37.90	18.70	25.20	27.40	23.77	29.30	32.40	33.40	31.70
Average	21.00	26.63	29.70	25.78	21.80	23.47	24.73	23.33	24.20	29.27	30.87	28.11	20.20	22.63	20.33	21.06
C-Lasso CCE																
20	19.50	19.70	17.70	18.97	10.60	11.50	9.70	10.60	30.90	35.80	33.60	33.43	9.50	10.70	10.20	10.13
50	15.40	11.70	12.50	13.20	20.90	21.90	19.20	20.67	20.40	23.50	27.90	23.93	15.80	17.30	16.50	16.53
100	13.30	13.70	14.10	13.70	28.20	38.20	38.30	34.90	18.70	24.80	24.30	22.60	27.20	27.40	26.50	27.03
Average	16.07	15.03	14.77	15.29	19.90	23.87	22.40	22.06	23.33	28.03	28.60	26.66	17.50	18.47	17.73	17.90

Table 1.8: Partially Heterogeneous Estimators – High Heterogeneity – DGP4, Case e: Low Spatial Dependence & Low Factor Dependence

	K = 2								*K = 3*							
T	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.45	0.25	-0.24	0.32	16.32	14.39	14.17	14.96	0.25	0.51	-0.19	0.32	15.52	13.86	13.57	14.32
50	-0.58	-0.22	-0.58	0.46	9.73	9.08	9.02	9.28	-0.47	-0.24	-0.61	0.44	9.38	8.71	8.53	8.87
100	0.31	-0.23	-0.36	0.30	7.16	6.51	6.51	6.73	0.24	-0.22	-0.29	0.25	6.98	6.35	6.35	6.56
Average	0.45	0.23	0.39	0.36	11.07	9.99	9.90	10.32	0.32	0.32	0.36	0.34	10.63	9.64	9.48	9.92
C-Lasso CCE																
20	2.56	3.79	3.46	3.27	14.32	14.40	14.20	14.31	2.36	4.57	4.22	3.72	14.34	14.57	14.39	14.43
50	2.94	3.64	3.17	3.25	9.84	9.81	9.36	9.67	3.89	5.05	5.00	4.65	9.78	10.22	9.95	9.98
100	3.48	2.71	3.25	3.15	8.06	7.25	7.25	7.52	4.08	4.81	5.40	4.76	7.99	7.81	8.16	7.99
Average	2.99	3.38	3.30	3.22	10.74	10.49	10.27	10.50	3.44	4.81	4.88	4.38	10.71	10.87	10.83	10.80
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	35.30	36.70	41.30	37.77	9.50	8.20	8.70	8.80	39.30	43.00	46.10	42.80	8.30	11.00	9.60	9.63
50	29.10	31.90	34.10	31.70	14.20	13.00	15.20	14.13	30.00	36.10	39.30	35.13	13.40	12.30	12.10	12.60
100	26.20	32.80	32.30	30.43	23.20	20.70	22.00	21.97	28.50	34.40	37.70	33.53	20.60	20.30	20.90	20.60
Average	30.20	33.80	35.90	33.30	15.63	13.97	15.30	14.97	32.60	37.83	41.03	37.16	14.10	14.53	14.20	14.28
C-Lasso CCE																
20	18.30	18.80	19.60	18.90	9.60	11.10	12.30	11.00	28.00	28.70	32.20	29.63	8.40	9.50	9.20	9.03
50	12.60	12.50	12.00	12.37	17.00	15.00	18.20	16.73	20.50	22.20	24.70	22.47	13.90	14.00	16.00	14.63
100	12.10	12.10	14.10	12.77	23.30	26.10	22.40	23.93	20.70	21.80	28.70	23.73	24.10	23.10	21.90	23.03
Average	14.33	14.47	15.23	14.68	16.63	17.40	17.63	17.22	23.07	24.23	28.53	25.28	15.47	15.53	15.70	15.57

Table 1.9: Partially Heterogeneous Estimators – High Heterogeneity – DGP4, Case g: High Spatial Dependence & Low Factor Dependence

	K = 2								*K = 3*							
T	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.74	0.30	-0.14	0.39	17.12	14.64	14.18	15.31	0.36	0.64	-0.29	0.43	16.97	14.55	14.08	15.20
50	-0.43	-0.34	-0.59	0.45	10.13	9.19	9.07	9.47	-0.40	-0.28	-0.75	0.47	9.95	8.89	8.67	9.17
100	0.27	-0.27	-0.42	0.32	7.47	6.61	6.57	6.88	0.30	-0.29	-0.40	0.33	7.34	6.34	6.42	6.70
Average	0.48	0.30	0.38	0.39	11.57	10.15	9.94	10.55	0.35	0.40	0.48	0.41	11.42	9.93	9.72	10.36
C-Lasso CCE																
20	3.29	3.78	2.13	3.07	16.72	14.55	13.87	15.05	2.50	4.21	3.15	3.29	16.60	14.47	13.81	14.96
50	3.13	2.86	2.50	2.83	10.32	9.71	9.28	9.77	2.99	3.71	4.32	3.67	10.05	9.32	9.52	9.63
100	3.55	2.86	2.75	3.05	8.64	7.62	7.28	7.85	3.90	4.08	4.79	4.26	8.28	7.62	7.98	7.96
Average	3.33	3.16	2.46	2.98	11.89	10.63	10.14	10.89	3.13	4.00	4.09	3.74	11.64	10.47	10.44	10.85
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	30.20	34.10	35.40	33.23	8.40	10.20	10.40	9.67	37.00	37.60	41.10	38.57	9.00	8.90	8.30	8.73
50	22.20	29.10	32.40	27.90	14.60	14.60	15.80	15.00	24.40	28.60	36.70	29.90	12.30	14.00	13.20	13.17
100	22.90	33.50	31.90	29.43	24.10	23.60	25.10	24.27	24.00	28.70	34.00	28.90	21.60	23.20	25.00	23.27
Average	25.10	32.23	33.23	30.19	15.70	16.13	17.10	16.31	28.47	31.63	37.27	32.46	14.30	15.37	15.50	15.06
C-Lasso CCE																
20	20.10	20.30	16.10	18.83	10.40	11.40	9.30	10.37	27.40	29.70	28.60	28.57	7.00	10.80	10.30	9.37
50	13.20	12.00	11.70	12.30	15.30	17.30	14.10	15.57	17.80	20.70	24.40	20.97	14.10	15.30	11.60	13.67
100	13.90	14.70	15.30	14.63	20.20	26.00	25.40	23.87	17.80	22.10	24.30	21.40	18.90	23.80	22.00	21.57
Average	15.73	15.67	14.37	15.26	15.30	18.23	16.27	16.60	21.00	24.17	25.77	23.64	13.33	16.63	14.63	14.87

Table 1.10: Forecasting Accuracy Measures, Low Heterogeneity – DGP4, Case e: Low Spatial Dependence & Low Factor Dependence

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	1.930	1.731	1.679	1.780	0.574	0.548	0.506	0.543	20	2.060	1.942	1.912	1.971	0.612	0.614	0.574	0.600
50	1.900	1.755	1.698	1.784	0.561	0.518	0.476	0.518	50	2.036	1.968	1.935	1.980	0.600	0.580	0.542	0.574
100	1.909	1.725	1.687	1.774	0.534	0.498	0.492	0.508	100	2.052	1.942	1.921	1.972	0.572	0.559	0.560	0.564
Average	1.913	1.737	1.688	1.779	0.557	0.521	0.491	0.523	Average	2.049	1.951	1.923	1.974	0.595	0.584	0.558	0.579
Ind. GLS									*2WFE*								
20	1.883	1.721	1.677	1.760	0.560	0.545	0.505	0.537	20	2.348	2.272	2.292	2.304	0.695	0.717	0.687	0.700
50	1.848	1.745	1.696	1.763	0.545	0.515	0.476	0.512	50	2.310	2.321	2.314	2.315	0.678	0.681	0.648	0.669
100	1.853	1.715	1.684	1.751	0.518	0.495	0.491	0.501	100	2.332	2.296	2.291	2.307	0.648	0.659	0.665	0.657
Average	1.861	1.727	1.685	1.758	0.541	0.518	0.491	0.517	Average	2.330	2.297	2.299	2.309	0.673	0.686	0.667	0.675
Ind. CCE									*CCEP*								
20	1.448	1.112	1.035	1.198	0.435	0.355	0.318	0.369	20	1.476	1.212	1.148	1.279	0.442	0.388	0.352	0.394
50	1.399	1.119	1.044	1.187	0.417	0.334	0.296	0.349	50	1.432	1.225	1.162	1.273	0.426	0.366	0.330	0.374
100	1.415	1.076	1.040	1.177	0.400	0.315	0.308	0.341	100	1.441	1.189	1.161	1.263	0.406	0.348	0.344	0.366
Average	1.421	1.103	1.040	1.188	0.417	0.335	0.307	0.353	Average	1.450	1.208	1.157	1.272	0.425	0.367	0.342	0.378
Ind. CCEX									*CCEPX*								
20	1.457	1.115	1.036	1.202	0.438	0.356	0.318	0.371	20	1.476	1.212	1.148	1.279	0.442	0.388	0.352	0.394
50	1.403	1.120	1.044	1.189	0.419	0.335	0.297	0.350	50	1.432	1.225	1.162	1.273	0.426	0.366	0.330	0.374
100	1.417	1.077	1.040	1.178	0.400	0.315	0.308	0.341	100	1.441	1.189	1.161	1.263	0.406	0.348	0.344	0.366
Average	1.426	1.104	1.040	1.190	0.419	0.335	0.308	0.354	Average	1.450	1.208	1.157	1.272	0.425	0.367	0.342	0.378
Ind. IPC									*IPCP*								
20	1.461	1.112	1.034	1.202	0.439	0.355	0.317	0.370	20	1.479	1.213	1.149	1.281	0.443	0.388	0.352	0.394
50	1.381	1.114	1.042	1.179	0.412	0.333	0.296	0.347	50	1.433	1.225	1.162	1.274	0.426	0.366	0.330	0.374
100	1.385	1.070	1.037	1.164	0.391	0.313	0.307	0.337	100	1.441	1.189	1.161	1.264	0.406	0.348	0.344	0.366
Average	1.409	1.099	1.037	1.182	0.414	0.334	0.307	0.351	Average	1.451	1.209	1.157	1.273	0.425	0.367	0.342	0.378
Ind. PCX									*PCPX*								
20	1.595	1.173	1.059	1.275	0.478	0.374	0.324	0.392	20	1.481	1.214	1.148	1.281	0.444	0.388	0.352	0.395
50	1.535	1.172	1.068	1.258	0.456	0.350	0.303	0.370	50	1.434	1.225	1.162	1.274	0.427	0.366	0.330	0.374
100	1.553	1.130	1.065	1.249	0.438	0.330	0.315	0.361	100	1.442	1.189	1.161	1.264	0.406	0.348	0.344	0.366
Average	1.561	1.158	1.064	1.261	0.457	0.351	0.314	0.374	Average	1.452	1.209	1.157	1.273	0.426	0.367	0.342	0.378
Ind. PCX2S									*PCPX2S*								
20	1.500	1.120	1.035	1.218	0.450	0.358	0.318	0.375	20	1.478	1.212	1.147	1.279	0.443	0.388	0.351	0.394
50	1.430	1.123	1.044	1.199	0.426	0.335	0.297	0.353	50	1.433	1.225	1.162	1.273	0.426	0.366	0.330	0.374
100	1.441	1.079	1.040	1.187	0.407	0.316	0.308	0.344	100	1.441	1.189	1.161	1.263	0.406	0.348	0.344	0.366
Average	1.457	1.107	1.040	1.201	0.428	0.336	0.307	0.357	Average	1.451	1.208	1.156	1.272	0.425	0.367	0.342	0.378

Table 1.11: Forecasting Accuracy Measures, Low Heterogeneity – DGP4, Case g: High Spatial Dependence & Low Factor Dependence

	Heterogeneous									*Homogeneous*							
T / N	RMSE				Theil's U					RMSE				Theil's U			
	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	2.653	2.205	2.197	2.352	0.703	0.638	0.604	0.649	20	2.667	2.356	2.375	2.466	0.705	0.681	0.650	0.679
50	2.411	2.250	2.178	2.280	0.657	0.610	0.566	0.611	50	2.463	2.404	2.362	2.410	0.669	0.651	0.612	0.644
100	2.378	2.128	2.145	2.217	0.622	0.575	0.578	0.592	100	2.440	2.295	2.328	2.355	0.636	0.619	0.626	0.627
Average	2.481	2.194	2.174	2.283	0.661	0.608	0.583	0.617	Average	2.524	2.352	2.355	2.410	0.670	0.650	0.630	0.650
Ind. GLS									*2WFE*								
20	2.567	2.191	2.194	2.317	0.679	0.634	0.603	0.639	20	3.046	2.777	2.846	2.890	0.807	0.804	0.782	0.797
50	2.332	2.234	2.175	2.247	0.634	0.605	0.565	0.602	50	2.734	2.762	2.770	2.755	0.741	0.748	0.720	0.736
100	2.294	2.114	2.141	2.183	0.599	0.571	0.577	0.582	100	2.699	2.635	2.690	2.675	0.701	0.709	0.722	0.711
Average	2.398	2.180	2.170	2.249	0.638	0.603	0.581	0.607	Average	2.826	2.725	2.768	2.773	0.750	0.754	0.741	0.748
Ind. CCE									*CCEP*								
20	2.374	1.772	1.747	1.964	0.633	0.517	0.486	0.545	20	2.326	1.825	1.814	1.989	0.619	0.533	0.504	0.552
50	2.110	1.811	1.715	1.878	0.579	0.494	0.449	0.507	50	2.043	1.859	1.782	1.895	0.559	0.507	0.467	0.511
100	2.088	1.662	1.686	1.812	0.549	0.453	0.459	0.487	100	2.001	1.718	1.755	1.825	0.525	0.468	0.478	0.490
Average	2.190	1.748	1.716	1.885	0.587	0.488	0.464	0.513	Average	2.123	1.801	1.784	1.903	0.568	0.503	0.483	0.518
Ind. CCEX									*CCEPX*								
20	2.465	1.789	1.754	2.003	0.658	0.522	0.487	0.556	20	2.326	1.825	1.814	1.989	0.619	0.533	0.504	0.552
50	2.146	1.819	1.718	1.895	0.589	0.496	0.450	0.512	50	2.043	1.859	1.782	1.895	0.559	0.507	0.467	0.511
100	2.108	1.666	1.688	1.820	0.554	0.454	0.459	0.489	100	2.001	1.718	1.755	1.825	0.525	0.468	0.478	0.490
Average	2.240	1.758	1.720	1.906	0.600	0.491	0.466	0.519	Average	2.123	1.801	1.784	1.903	0.568	0.503	0.483	0.518
Ind. IPC									*IPCP*								
20	2.325	1.767	1.749	1.947	0.620	0.516	0.486	0.540	20	2.326	1.827	1.816	1.990	0.619	0.533	0.504	0.552
50	2.045	1.802	1.716	1.854	0.561	0.491	0.449	0.501	50	2.043	1.859	1.783	1.895	0.559	0.507	0.467	0.511
100	2.011	1.655	1.687	1.785	0.529	0.451	0.459	0.480	100	2.001	1.718	1.756	1.825	0.525	0.468	0.478	0.490
Average	2.127	1.742	1.718	1.862	0.570	0.486	0.465	0.507	Average	2.124	1.801	1.785	1.903	0.568	0.503	0.483	0.518
Ind. PCX									*PCPX*								
20	2.558	1.830	1.769	2.052	0.682	0.534	0.491	0.569	20	2.332	1.827	1.815	1.991	0.621	0.533	0.504	0.553
50	2.230	1.854	1.734	1.939	0.611	0.505	0.454	0.523	50	2.045	1.859	1.783	1.896	0.560	0.507	0.467	0.511
100	2.196	1.701	1.703	1.867	0.577	0.464	0.463	0.501	100	2.002	1.718	1.755	1.825	0.525	0.468	0.478	0.490
Average	2.328	1.795	1.735	1.953	0.623	0.501	0.470	0.531	Average	2.126	1.802	1.784	1.904	0.569	0.503	0.483	0.518
Ind. PCX2S									*PCPX2S*								
20	2.417	1.777	1.746	1.980	0.644	0.518	0.485	0.549	20	2.326	1.825	1.814	1.989	0.619	0.533	0.504	0.552
50	2.138	1.811	1.714	1.888	0.586	0.494	0.449	0.510	50	2.044	1.859	1.782	1.895	0.559	0.507	0.467	0.511
100	2.116	1.664	1.686	1.822	0.556	0.454	0.459	0.490	100	2.001	1.718	1.755	1.825	0.525	0.468	0.478	0.490
Average	2.224	1.751	1.715	1.896	0.596	0.489	0.464	0.516	Average	2.124	1.801	1.784	1.903	0.568	0.503	0.483	0.518

Table 1.12: Forecasting Accuracy Measures, High Heterogeneity – DGP4, Case e: Low Spatial Dependence & Low Factor Dependence

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	1.930	1.731	1.679	1.780	0.575	0.545	0.503	0.541	20	2.206	2.082	2.050	2.113	0.655	0.653	0.610	0.639
50	1.900	1.755	1.698	1.784	0.561	0.516	0.476	0.518	50	2.186	2.112	2.074	2.124	0.642	0.620	0.580	0.614
100	1.909	1.725	1.687	1.774	0.535	0.497	0.492	0.508	100	2.204	2.087	2.062	2.118	0.615	0.600	0.599	0.605
Average	1.913	1.737	1.688	1.779	0.557	0.520	0.490	0.522	Average	2.199	2.094	2.062	2.118	0.637	0.624	0.596	0.619
Ind. GLS									*2WFE*								
20	1.894	1.724	1.678	1.765	0.563	0.543	0.502	0.536	20	2.523	2.421	2.443	2.462	0.745	0.757	0.725	0.742
50	1.860	1.748	1.697	1.768	0.548	0.514	0.476	0.513	50	2.480	2.489	2.475	2.481	0.724	0.726	0.691	0.714
100	1.865	1.718	1.685	1.756	0.522	0.495	0.491	0.503	100	2.503	2.461	2.455	2.473	0.694	0.703	0.709	0.702
Average	1.873	1.730	1.686	1.763	0.545	0.518	0.490	0.517	Average	2.502	2.457	2.458	2.472	0.721	0.729	0.708	0.719
Ind. CCE									*CCEP*								
20	1.450	1.113	1.036	1.200	0.436	0.354	0.316	0.369	20	1.594	1.322	1.253	1.390	0.478	0.421	0.381	0.426
50	1.400	1.120	1.044	1.188	0.417	0.334	0.297	0.349	50	1.559	1.338	1.271	1.389	0.462	0.399	0.361	0.407
100	1.415	1.076	1.040	1.177	0.400	0.315	0.308	0.341	100	1.569	1.306	1.272	1.382	0.442	0.382	0.376	0.400
Average	1.422	1.103	1.040	1.188	0.418	0.334	0.307	0.353	Average	1.574	1.322	1.265	1.387	0.461	0.400	0.373	0.411
Ind. CCEX									*CCEPX*								
20	1.457	1.115	1.036	1.202	0.439	0.355	0.316	0.370	20	1.594	1.322	1.253	1.390	0.478	0.421	0.381	0.426
50	1.403	1.120	1.044	1.189	0.418	0.334	0.297	0.350	50	1.559	1.338	1.271	1.389	0.462	0.399	0.361	0.407
100	1.417	1.077	1.040	1.178	0.401	0.315	0.308	0.341	100	1.569	1.306	1.272	1.382	0.442	0.382	0.376	0.400
Average	1.426	1.104	1.040	1.190	0.419	0.335	0.307	0.354	Average	1.574	1.322	1.265	1.387	0.461	0.400	0.373	0.411
Ind. IPC									*IPCP*								
20	1.461	1.112	1.034	1.202	0.439	0.354	0.315	0.369	20	1.599	1.324	1.255	1.393	0.479	0.421	0.381	0.427
50	1.381	1.114	1.042	1.179	0.412	0.332	0.296	0.347	50	1.560	1.340	1.272	1.391	0.462	0.399	0.361	0.407
100	1.385	1.070	1.037	1.164	0.392	0.313	0.307	0.337	100	1.570	1.307	1.272	1.383	0.442	0.382	0.376	0.400
Average	1.409	1.099	1.037	1.182	0.414	0.333	0.306	0.351	Average	1.576	1.324	1.267	1.389	0.461	0.400	0.373	0.411
Ind. PCX									*PCPX*								
20	1.595	1.173	1.059	1.275	0.478	0.373	0.323	0.391	20	1.599	1.324	1.253	1.392	0.479	0.421	0.381	0.427
50	1.535	1.172	1.068	1.258	0.456	0.349	0.303	0.370	50	1.561	1.339	1.271	1.390	0.463	0.399	0.361	0.408
100	1.553	1.130	1.065	1.249	0.438	0.330	0.315	0.361	100	1.570	1.307	1.272	1.383	0.442	0.382	0.376	0.400
Average	1.561	1.158	1.064	1.261	0.458	0.351	0.314	0.374	Average	1.576	1.323	1.265	1.388	0.461	0.401	0.373	0.412
Ind. PCX2S									*PCPX2S*								
20	1.500	1.120	1.035	1.218	0.451	0.356	0.316	0.374	20	1.596	1.322	1.252	1.390	0.478	0.420	0.381	0.426
50	1.430	1.123	1.044	1.199	0.426	0.335	0.297	0.353	50	1.559	1.338	1.271	1.390	0.462	0.399	0.361	0.407
100	1.441	1.079	1.040	1.187	0.408	0.316	0.308	0.344	100	1.569	1.306	1.272	1.382	0.442	0.382	0.376	0.400
Average	1.457	1.107	1.040	1.201	0.428	0.336	0.307	0.357	Average	1.575	1.322	1.265	1.387	0.461	0.400	0.373	0.411

Table 1.13: Forecasting Accuracy Measures, High Heterogeneity – DGP4, Case g: High Spatial Dependence & Low Factor Dependence

	Heterogeneous									*Homogeneous*							
	RMSE				Theil's U					RMSE				Theil's U			
N \ T	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	2.653	2.205	2.197	2.352	0.701	0.634	0.599	0.645	20	2.785	2.477	2.491	2.584	0.733	0.709	0.675	0.706
50	2.411	2.250	2.178	2.280	0.654	0.607	0.564	0.608	50	2.592	2.527	2.481	2.533	0.699	0.679	0.640	0.673
100	2.378	2.128	2.145	2.217	0.620	0.573	0.576	0.590	100	2.573	2.422	2.450	2.482	0.668	0.650	0.655	0.658
Average	2.481	2.194	2.174	2.283	0.659	0.605	0.580	0.614	Average	2.650	2.475	2.474	2.533	0.700	0.679	0.657	0.679
Ind. GLS									*2WFE*								
20	2.585	2.194	2.195	2.325	0.682	0.630	0.598	0.637	20	3.187	2.903	2.972	3.021	0.839	0.831	0.807	0.826
50	2.348	2.239	2.176	2.254	0.636	0.603	0.563	0.601	50	2.883	2.908	2.908	2.900	0.775	0.780	0.751	0.769
100	2.310	2.118	2.142	2.190	0.602	0.570	0.575	0.582	100	2.851	2.782	2.834	2.822	0.738	0.744	0.755	0.746
Average	2.414	2.184	2.171	2.256	0.640	0.601	0.579	0.607	Average	2.974	2.864	2.905	2.914	0.784	0.785	0.771	0.780
Ind. CCE									*CCEP*								
20	2.375	1.773	1.748	1.965	0.631	0.513	0.482	0.542	20	2.407	1.904	1.887	2.066	0.638	0.551	0.519	0.570
50	2.110	1.811	1.715	1.879	0.576	0.491	0.448	0.505	50	2.138	1.940	1.860	1.979	0.581	0.526	0.485	0.531
100	2.088	1.662	1.686	1.812	0.548	0.452	0.457	0.486	100	2.100	1.805	1.835	1.913	0.549	0.490	0.497	0.512
Average	2.191	1.749	1.716	1.885	0.585	0.486	0.462	0.511	Average	2.215	1.883	1.861	1.986	0.590	0.523	0.501	0.538
Ind. CCEX									*CCEPX*								
20	2.465	1.789	1.754	2.003	0.656	0.518	0.484	0.553	20	2.407	1.904	1.887	2.066	0.638	0.551	0.519	0.570
50	2.146	1.819	1.718	1.895	0.586	0.494	0.449	0.509	50	2.138	1.940	1.860	1.979	0.581	0.526	0.485	0.531
100	2.108	1.666	1.688	1.820	0.553	0.453	0.457	0.488	100	2.100	1.805	1.835	1.913	0.549	0.490	0.497	0.512
Average	2.240	1.758	1.720	1.906	0.598	0.488	0.463	0.517	Average	2.215	1.883	1.861	1.986	0.590	0.523	0.501	0.538
Ind. IPC									*IPCP*								
20	2.325	1.767	1.749	1.947	0.618	0.512	0.482	0.537	20	2.409	1.907	1.890	2.069	0.638	0.552	0.520	0.570
50	2.045	1.802	1.716	1.854	0.559	0.489	0.448	0.498	50	2.139	1.941	1.861	1.980	0.581	0.526	0.485	0.531
100	2.011	1.655	1.687	1.785	0.528	0.450	0.457	0.478	100	2.101	1.806	1.836	1.914	0.549	0.490	0.497	0.512
Average	2.127	1.742	1.718	1.862	0.568	0.484	0.463	0.505	Average	2.216	1.885	1.862	1.988	0.590	0.523	0.501	0.538
Ind. PCX									*PCPX*								
20	2.558	1.830	1.769	2.052	0.679	0.530	0.488	0.566	20	2.413	1.906	1.888	2.069	0.640	0.552	0.519	0.570
50	2.230	1.854	1.734	1.939	0.608	0.503	0.453	0.521	50	2.140	1.941	1.860	1.980	0.582	0.526	0.485	0.531
100	2.196	1.701	1.703	1.867	0.576	0.462	0.462	0.500	100	2.101	1.806	1.835	1.914	0.550	0.490	0.497	0.512
Average	2.328	1.795	1.735	1.953	0.621	0.498	0.467	0.529	Average	2.218	1.884	1.861	1.988	0.591	0.523	0.501	0.538
Ind. PCX2S									*PCPX2S*								
20	2.417	1.777	1.746	1.980	0.642	0.515	0.482	0.546	20	2.408	1.904	1.887	2.066	0.638	0.551	0.519	0.570
50	2.138	1.811	1.714	1.888	0.583	0.491	0.447	0.507	50	2.139	1.940	1.860	1.980	0.582	0.526	0.485	0.531
100	2.116	1.664	1.686	1.822	0.556	0.452	0.457	0.488	100	2.100	1.805	1.835	1.914	0.549	0.490	0.497	0.512
Average	2.224	1.751	1.715	1.896	0.594	0.486	0.462	0.514	Average	2.216	1.883	1.860	1.986	0.590	0.523	0.501	0.538

Chapter 2

Equal Predictive Ability Tests for Panel Data[1]

In previous chapter, the comparison of homogeneous and heterogeneous estimators was done by means of Monte Carlo simulations. In practice, comparison of different methods of prediction have to be made using a sample of observations. This chapter proposes novel tests for equal predictive ability in panels of forecasts allowing for different types and strength of cross-sectional dependence across units. We compare the predictive ability of two forecasters using forecast errors from different units correlated via common factors and spatial spillovers. We compute size and power of these tests in finite samples by means of an extensive Monte Carlo study finding very good small sample properties. Finally, we apply the tests to compare the economic growth predictions of the Organisation for Economic Co-operation and Development (OECD) and IMF.

[1]This chapter is based on a paper written with Alain Pirotte, Giovanni Urga and Zhenlin Yang submitted to Journal of Business & Economic Statistics.

2.1 Introduction

Formal tests of the null hypothesis of no difference in the forecast accuracy using two time series of forecast errors have been widely discussed in the literature and formalized, for instance, by Vuong (1989), Diebold and Mariano (1995, hereafter DM), West (1996), Clark and McCracken (2001), Giacomini and White (2006, hereafter GW), Clark and West (2007), Clark and McCracken (2015), among others. Whereas the literature in panel data taking into consideration the specific challenges such as heterogeneity and cross-sectional dependence (CD) is scarce, with a few exceptions. First is Davies and Lahiri (1995, hereafter DL) who focus on testing unbiasedness and efficiency of forecasts made by several different agents for the same unit. Their analysis is based on a three dimensional panel data regression where the dimensions are agents generating the forecasts, target years and forecast horizons. Second is undertaken by Timmermann and Zhu (2019) who focus on predictions produced for several different units but their framework is based mostly on tests which use a single cross-section of forecasts or on cross-sectional aggregates of a panel of prediction errors.

The main aim of this chapter is to propose tests for the equal predictive ability (EPA) hypothesis for panel data taking into account both the time series and the cross-sections features of the data. We propose tests allowing to compare the predictive ability of two forecasters, based on n units, hence n pairs of time series of observed forecast errors of length T, from their forecasts on an economic variable. Various panel data tests of EPA are proposed, extending that of DM which concerns a single time series. Contrary to DL, our tests are developed for forecasts made for different panel units.

We develop two types of tests of predictive ability. The first one focuses on EPA on average over all panel units and over time. This test is useful and of economic importance when the researcher is not interested in the differences of predictive ability for a specific unit but the overall differences. In the second type of tests, to deal with possible heterogeneity, we focus on the null hypothesis which states that the EPA holds for each panel unit. To deal with weak cross-sectional dependence (WCD) and strong cross-sectional dependence (SCD), we follow the recent literature on principal components (PC) analysis of large dimensional factor models (Bai and Ng, 2002; Bai, 2003) and covariance matrix estimation methods which are robust to spatial dependence Kelejian and Prucha (2007, hereafter KP). Following DM, we motivate our test statistics with assumptions on the loss differentials themselves and not on the models or methods of forecasting, as in West (1996) and GW, neither on their cross-sectional averages as in Timmermann and Zhu (2019).

We investigate the small sample properties of the tests proposed via an extensive Monte Carlo simulation exercise. For the treatment of spatial dependence in the errors, we follow KP and use spatial heteroskedasticity and autocorrelation consistent (SHAC) estimators of the covariance matrix. In a time series framework the small sample properties of heteroskedasticity and autocorrelation consistent estimators are well known and comparison of the role of different kernel functions in the estimation performance is readily available (see Andrews, 1991). Whereas, in spatial modeling the Monte Carlo analysis on SHAC estimators is limited to only KP. Here, their analysis is extended in several dimensions, such that we consider many different combinations of time and cross-sectional dimension sizes and allow for several different kernel functions to investigate their role on small sample properties of the EPA tests.

Finally, the chapter contributes also to the empirical literature. These tests are applied to compare the economic growth forecasts errors of the OECD and the International Monetary Fund (IMF). We investigate the equality of accuracy for different time periods and country samples.

The remainder of the chapter is as follows: In Section 2.2, we present our motivation for developing tests of EPA for panel data and the hypotheses of interest. In Section 2.3, the original time series DM test is briefly reviewed and statistics for panel tests of EPA are stated. Section 2.4 investigates the small sample properties of these new tests. In Section 2.5, the predictive ability of the OECD and IMF are compared using their economic growth forecasts. Sections 2.6 concludes.

2.2 Forecasting and Predictive Accuracy: Motivation and General Principle

2.2.1 Motivation

The applied literature in comparing the accuracy of two or more forecasts with panel data is typically based on the classical indicators instead of formal statistical tests. Pons (2000) compares the economic growth forecasts made by the IMF and the OECD using data from G7 countries but remained in the time series context by analyzing the forecast errors for each country separately. They used unbiasedness tests, root mean squared error (RMSE), mean absolute error (MAE) and Theil's U for comparing the forecasts of the two institutions. Vuchelen and Gutierrez (2005) also apply country by country analysis on the OECD macroeconomic forecast errors and used statistical tests to investigate the informational content of the forecasts. Merola and Pérez (2013) use data from 15 countries to compare the fiscal forecast errors of national governments and international agencies. They applied regression methods on the forecast errors to compare the biases in these forecasts but did not compare the efficiency of forecasts. Dreher et al. (2008) focus on the IMF economic growth and inflation forecasts using data from 157 countries. Their analysis is also based on panel regressions and they explore the bias and efficiency of the forecasts.

These studies suggest some stylized facts about the forecasts made by international organizations: (i) the forecast errors of different countries are affected by common global shocks, (ii) for countries which are closer to each other the comovement of the forecast errors are stronger, and (iii) international agencies make systematic errors for some particular groups of countries.

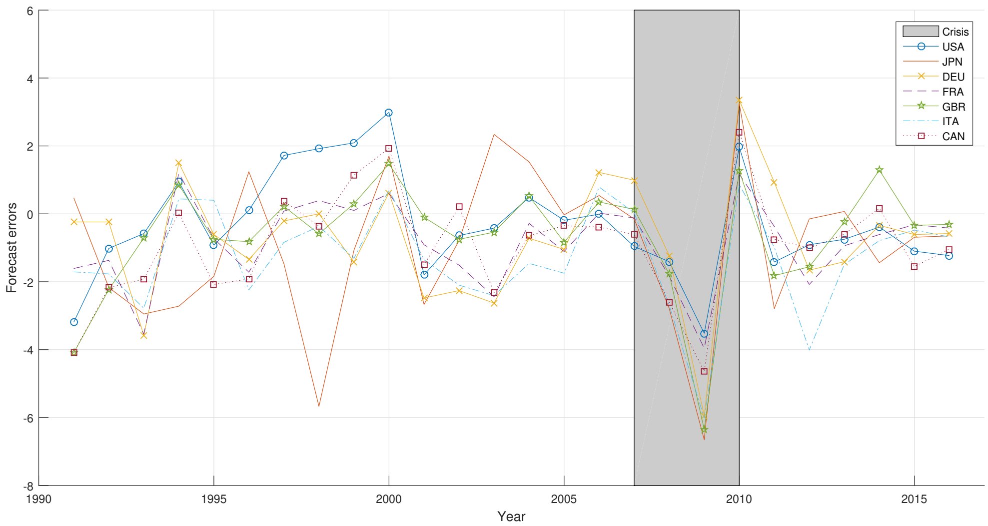
Common Factors. It is clear that during the times like economic crisis periods forecasting gets more difficult. Pain et al. (2014) found that the economic growth of the OECD countries for the period 2007-2012 was systematically over-predicted by the organization, in particular for the European economies. This suggests that there are global common factors affecting the magnitude of forecast errors. Furthermore, the effect of these common shocks is heterogeneous across economies, e.g., it is higher for the European economies. Figure 2.1 shows the one-year ahead forecast errors by OECD and IMF between 1991-2016 for the G7 countries. In both panels, it is seen that during the crisis and recovery period the correlation between the forecast errors across countries is very high, such that they go down together during the height of the crisis and up during the recovery. In terms of modeling, this suggests a common factor structure for the forecast errors.

Spatial Interactions. The dependence between the forecast errors across countries is not the same for each group of countries. Table 2.1 shows the pairwise correlation coefficients between the time series given in Figure 2.1. The highest correlations occur between the European economies. For instance, in the case of the OECD forecast errors, FRA-ITA, DEU-FRA and DEU-ITA pairs show a correlation coefficient around 0.85. It is very high also between the two North American countries with the USA-CAN correlation coefficient being 0.85. The lowest correlation is between JPN-FRA which is followed by other pairs involving JPN. This suggests that the forecast errors are more strongly correlated for countries closer to each other. In terms of modeling, this implies that there are spatial dependencies across forecast errors.

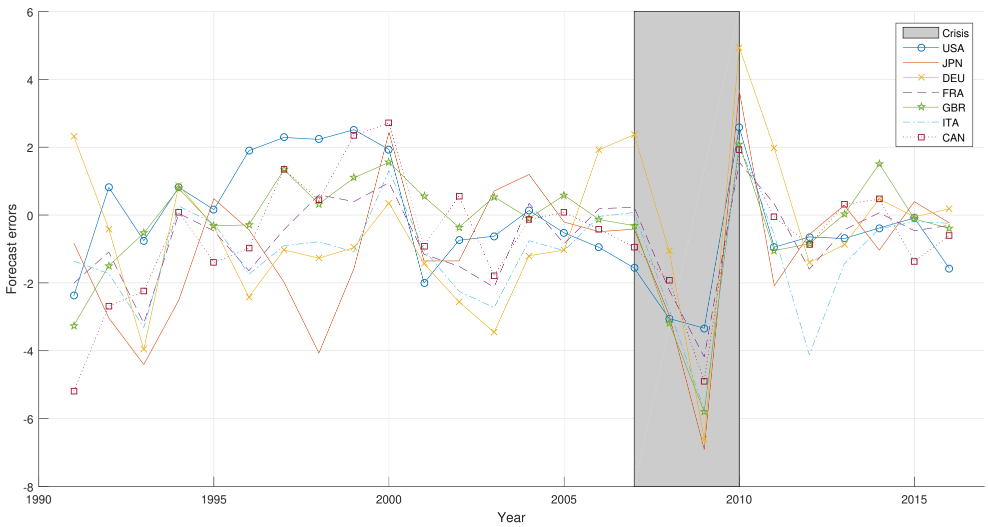
Heterogeneity. The forecast ability of an organization is not the same for each country. In fact, the arguments in the part on common factors had already suggested that for some countries the errors can be systematically different from others. However, that was the result of time varying common factors, such as economic crisis, which may not be the only source of heterogeneity across countries. Dreher et al. (2008) find that for the case of economic growth, IMF forecasts are significantly downward biased for non-OECD countries while the bias is positive for OECD countries. They further find evidence of time-invariant country fixed effects in the forecast errors. The results on the inflation forecasts are similar. In terms of modeling, this suggests that heterogeneity should be controlled for in the tests of predictive ability.

2.2.2 Setup in the Context of Panel Data

We are interested in τ-steps ahead observed forecast errors of a variable $y_{i,t}$, for time $t = 1, 2, \dots, T$, units $i = 1, 2, \dots, n$.



(a) OECD



(b) IMF

Figure 2.1: One-year Ahead OECD and IMF Economic Growth Forecast Errors, 1991-2016, G7 Countries

Table 2.1: Cross-country correlations in one-year ahead OECD (a) and IMF (b) economic growth forecast errors, 1991-2016, G7 countries

	USA	JPN	DEU	FRA	GBR	ITA	CAN
USA	1.000						
JPN	0.320	1.000					
DEU	0.501	0.431	1.000				
FRA	0.670	0.289	0.862	1.000			
GBR	0.753	0.495	0.581	0.712	1.000		
ITA	0.564	0.368	0.852	0.883	0.747	1.000	
CAN	0.846	0.403	0.616	0.762	0.831	0.643	1.000

(a) Computed from OECD forecasts

	USA	JPN	DEU	FRA	GBR	ITA	CAN
USA	1.000						
JPN	0.340	1.000					
DEU	0.233	0.579	1.000				
FRA	0.611	0.605	0.752	1.000			
GBR	0.711	0.611	0.400	0.731	1.000		
ITA	0.509	0.669	0.819	0.895	0.699	1.000	
CAN	0.699	0.486	0.341	0.777	0.841	0.615	1.000

(b) Computed from IMF forecasts

In terms of the analysis of forecasts using panel data, this chapter is somewhat related to the work of DL, Lahiri and Sheng (2010) and Driver et al. (2013) and generalizes them in several dimensions. The focus of DL is on testing unbiasedness and efficiency of forecasts made by several different agents for the same panel unit. Their analysis is based on a three dimensional panel data regression where the dimensions are agents generating the forecasts, target years and forecast horizons. In our case, we have different target values to be forecast which are the realizations of the same variable for different units. For example, in their application they use data on forecasts of the growth rate of the USA gross national product made by 35 forecasters for 16 different years and 11 time horizons. On our side, the framework consists of forecasts made by two forecasters for the same variable (like gross national product growth rate) from different units, possibly for different horizons. The model of DL for the forecast errors can be written as

$$e_{l,t} = y_t - \widehat{y}_{l,t} = \lambda_l + f_t + u_{l,t} \tag{2.1}$$

where $e_{l,t}$ is the forecast error made by the forecaster l at time t for the value of τ-steps ahead variable y_t where for simplicity we assume that there is only one forecast horizon available. Notice that the target variable has only the time index. Importantly, they are interested in *the magnitude of the forecast errors.* They considered the forecaster specific bias term λ_l and the common shock variable f_t which affects the errors of each forecaster. They assumed that $u_{l,t}$ is uncorrelated over l and t but heteroskedastic over l. In our setup, we are interested in *the loss differential associated with the forecast errors* and the error component structure is generalized, such that its components enter the equation interactively.

As an example to see why this is relevant, let us assume that the loss is quadratic and the forecasts in the model (2.1) are unbiased such that the expectations of each component in the model are zero, i.e. $\mathrm{E}(\lambda_l) = \mathrm{E}(f_t) = \mathrm{E}(u_{l,t}) = 0$. Then the conditional expectation of the squared errors given λ_l and f_t is

$$\mathrm{E}(e_{l,t}^2 | \lambda_l, f_t) = \boldsymbol{\theta}_l' \mathbf{g}_t, \tag{2.2}$$

where $\theta_l' = (\lambda_l^2 + \sigma_l^2, 2\lambda_l, 1)$, $\mathbf{g}_t = (1, f_t, f_t^2)'$ and $\mathrm{E}(u_{l,t}^2) = \sigma_l^2$. Hence, the conditional expectation function of the squared errors has a factor structure with three factors.

We generalize this setting assuming that the loss differential of the errors take the form

$$\Delta L_{i,t} = L\left(e_{1i,t}\right) - L\left(e_{2i,t}\right) = \mu_i + v_{i,t}, \tag{2.3}$$

$$v_{i,t} = \boldsymbol{\lambda}_i' \mathbf{f}_t + \varepsilon_{i,t}, \tag{2.4}$$

$$\varepsilon_{i,t} = \sum_{j=1}^{n} r_{ij} \epsilon_{j,t}, \tag{2.5}$$

where $L(\cdot)$ is a generic loss function, $e_{li,t}$ is the forecast error made by the forecaster $l = 1, 2$ at time t for the τ-steps ahead variable for unit $i = 1, 2, \ldots, n$, therefore they forecast $y_{li,t}$, $t = 1, 2, \ldots, T$. $\mathbf{f}_t$ is an $m \times 1$ vector of unobservable common factors and $\boldsymbol{\lambda}_i$ is the associated $m \times 1$ vector of the factor loadings. The coefficients r_{ij} are fixed but unknown elements of an $n \times n$ matrix $\mathbf{R}_n$. These elements are possibly functions of a smaller set of parameters. This is a general specification which contains as special cases all commonly used spatial processes like spatial autoregression (SAR), spatial moving average (SMA), and spatial error components (SEC) as well as higher order SAR or SMA processes. The variables $\mathbf{f}_t$ and $\epsilon_{i,t}$ are assumed to have zero mean but allowed to be autocorrelated through time. Then, assuming that μ_i are fixed parameters, a hypothesis of interest is

$$H_{0,1} : \bar{\mu} = 0, \tag{2.6}$$

where $\bar{\mu} = \frac{1}{n} \sum_{i=1}^{n} \mu_i$. This hypothesis states that the forecasts generated by the two agents are equally accurate on average over all $i = 1, 2, \ldots, n$ and $t = 1, 2, \ldots, T$. It looks plausible to consider this in a micro forecasting study where the units can be seen as random draws from a population. If the researcher is not interested in the difference in predictive ability for any particular unit but the predictive ability on average, this hypothesis should be considered.

In a macro forecasting study, the differences for each unit can have a specific economic importance and may be of interest from a policy perspective. For instance, a question of interest is whether the forecasts made by agents are more accurate for a particular group of countries or all countries in the sample. In this case, the null hypothesis can be formulated such that the predictive equality holds for each unit as

$$H_{0,2} : \mathrm{E}(\Delta L_{i,t}) = \mu_i = 0, \text{ for all } i = 1, 2, \ldots, n. \tag{2.7}$$

Throughout the text, we assume that μ_i and factor loadings $\boldsymbol{\lambda}_i$ are fixed parameters, whereas common factors $\mathbf{f}_t$ are random variables.

2.3 Tests for Equal Predictive Ability for Panel Data

In this section, we present a generalization of the DM test to panel data by proposing tests of overall EPA given in (2.6) (Section 2.3.1) and tests of joint EPA given in (2.7) (Section 2.3.2), taking into account several possible forms of CD.

Let $L(\cdot)$ denote a general loss function and the loss differential between two forecast errors be $\Delta L_{i,t} = L(e_{1i,t}) - L(e_{2i,t})$ for unit $i = 1, 2, \ldots, n$ and time $t = 1, 2, \ldots, T$. Under weak stationarity of the loss differential series, for each unit i, the asymptotic distribution of the sample mean of the loss differential series can be obtained as follows

$$\sqrt{T}\left(\Delta \bar{L}_{i,T} - \mu_i\right) \xrightarrow{D} N(0, \sigma_i^2), \tag{2.8}$$

where $\Delta \bar{L}_{i,T} = \frac{1}{T}\sum_{t=1}^{T} \Delta L_{i,t}$, $\mu_i = \mathrm{E}(\Delta L_{i,t})$,

$$\sigma_i^2 = \sum_{s=-\infty}^{\infty} \gamma_{v_i}(s), \tag{2.9}$$

with $\gamma_{v_i}(s) = \mathrm{E}(v_{i,t}v_{i,t-s})$ and $\xrightarrow{D}$ signifies convergence in distribution. The hypothesis of interest is the EPA on average

$$H_0 : E(\Delta L_{i,t}) = 0. \tag{2.10}$$

From (2.8) and (2.10), we derive the DM test statistic for testing the equality of forecast accuracy between the two competing series as

$$S_{i,T}^{(0)} = \frac{\Delta \bar{L}_{i,T}}{\hat{\sigma}_{i,T}/\sqrt{T}} \xrightarrow{D} N(0, 1), \tag{2.11}$$

where $\hat{\sigma}_{i,T}^2$ is a consistent estimate of σ_i^2. Originally DM suggested using the non-parametric variance estimator (see, for instance, Andrews, 1991) with truncated kernel to construct the variance estimates but this may result in non-positive variance estimates. [See Section 1.1 of DM and the discussions in the following subsection.] Below we allow for other kernel functions.

It is possible to relax the weak stationarity assumption and allow for nonstationary processes by considering mixing processes as in the work of GW. They prove the consistency of the test for general mixing processes and alternative hypotheses. Our generalizations of the DM test, however, are to a panel data framework.

2.3.1 Tests for Overall Equal Predictive Ability

Consider the sample mean loss differential over time and units:

$$\Delta\bar{L}_{n,T} = \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}\Delta L_{i,t}. \tag{2.12}$$

We provide testing procedures for overall EPA implied in (2.6) based on $\Delta\bar{L}_{n,T}$. Under regularity, this statistic satisfies a central limit theorem (CLT) given by

$$\sqrt{nT}(\Delta\bar{L}_{n,T} - \bar{\mu}_n)/\sigma_{n,T} \xrightarrow{D} N(0,1), \tag{2.13}$$

where $\bar{\mu}_n = n^{-1}\sum_{i=1}^{n}\mu_i$ and

$$\sigma^2_{n,T} = \frac{1}{nT}\sum_{i,j=1}^{n}\sum_{t,s=1}^{T}\mathrm{E}(v_{i,t}v_{j,s}).$$

The case of no CD. Suppose that the loss differential is generated by (2.3) and (2.4) with $\boldsymbol{\lambda}_i'\mathbf{f}_t = 0$ and $r_{ij} = 0$ for every $i \neq j$. If weak stationarity assumption is satisfied for each i, a sequential application of the CLT for weakly stationary time series (see, e.g., Anderson, 1971, Theorem 7.7.8) and the CLT for independent but heterogeneous sequence (see, e.g., White, 2001, Theorem 5.10) provides the result in (2.13) with $\sigma^2_{n,T} = \bar{\sigma}^2_n = n^{-1}\sum_{i=1}^{n}\sigma^2_i$. The conditions for this result to be valid can be seen by writing $\sqrt{nT}(\Delta\bar{L}_{n,T} - \bar{\mu}_n)$ as $\frac{1}{\sqrt{n}}\sum_{i=1}^{n}\sqrt{T}(\Delta\bar{L}_{i,T} - \mu_i)$, where $\Delta\bar{L}_{i,T} = \frac{1}{T}\sum_{t=1}^{T}\Delta L_{i,t}$. As $T \to \infty$, $\sqrt{T}(\Delta\bar{L}_{i,T} - \mu_i) \xrightarrow{D} Z_i$, where $Z_i \sim N(0, \sigma^2_i)$, under weak stationarity assumption as in (2.8). Then, the convergence of $\frac{1}{\sqrt{n}}\sum_{i=1}^{n} Z_i/\bar{\sigma}_n$, as $n \to \infty$, follows from Theorem 5.10 of

White (2001), provided that $\{Z_i\}_{i=1}^n$ are independent as they are, $E|Z_i|^{2+\delta} < C < \infty$ for some $\delta > 0$ for all i, and $\bar{\sigma}_n^2 > \delta' > 0$ for all n sufficiently large.

Suppose that we want to test hypothesis (2.6). We consider the test statistic

$$S_{n,T}^{(1)} = \frac{\Delta \bar{L}_{n,T}}{\hat{\bar{\sigma}}_{n,T}/\sqrt{nT}} \xrightarrow{D} N(0,1), \tag{2.14}$$

where $\hat{\bar{\sigma}}_{n,T}^2 = n^{-1}\sum_{i=1}^n \hat{\sigma}_{i,T}^2$, and $\hat{\sigma}_{i,T}^2$ is a consistent estimate of σ_i^2 based on the ith time series of loss differentials

$$\hat{\sigma}_{i,T}^2 = \frac{1}{T}\sum_{t,s=1}^{T} k_T\left(\frac{|t-s|}{l_T+1}\right)\Delta\tilde{L}_{i,t}\Delta\tilde{L}_{i,s}, \tag{2.15}$$

where $\Delta\tilde{L}_{i,t} = \Delta L_{i,t} - \Delta\bar{L}_{i,T}$ and $k_T(\cdot)$ is the time series kernel function. Under general conditions Andrews (1991) showed that $\hat{\sigma}_{i,T}^2 \xrightarrow{p} \sigma_i^2$ as $T \to \infty$ with $l_T \to \infty$, $l_T = o(T)$. If the conditions implying $\hat{\sigma}_{i,T}^2 \xrightarrow{p} \sigma_i^2$ are satisfied, it immediately follows that $\hat{\bar{\sigma}}_{n,T}^2 - \sigma_{n,T}^2 \xrightarrow{p} 0$ from which the asymptotic distribution for the test statistic given in (2.14) is obtained under the null hypothesis (2.6).

The case of WCD. Suppose that in (2.3) and (2.4), $\boldsymbol{\lambda}_i'\mathbf{f}_t = 0$ but $r_{ij} \neq 0$ for some $i \neq j$. In this case of WCD, the loss differentials $\Delta L_{i,t}$ are no longer independent across i, and therefore, the variance estimator $\hat{\bar{\sigma}}_{n,T}^2$ given above is no longer valid. Nevertheless the CLT in (2.13) still satisfied with

$$\sigma_{n,T}^2 = \frac{1}{nT}\sum_{i,j=1}^{n}\sum_{t,s=1}^{T}\mathbf{r}_{i.}'\boldsymbol{\gamma}_{\epsilon_i}(|t-s|)\mathbf{r}_{j.},$$

where $\boldsymbol{\gamma}_{\epsilon_i}(|t-s|) = \text{diag}[\gamma_{\epsilon_1}(|t-s|), \gamma_{\epsilon_2}(|t-s|), \ldots, \gamma_{\epsilon_n}(|t-s|)]$, $\gamma_{\epsilon_i}(s) = \text{E}(\epsilon_{i,t}\epsilon_{i,t-s})$. To see this, write $\sqrt{nT}(\Delta\bar{L}_{n,T} - \bar{\mu}_n)$ as $\frac{1}{\sqrt{n}}\sum_{i=1}^n \sqrt{T}(\Delta\bar{L}_{i,T} - \mu_i) = \frac{1}{\sqrt{n}}\sum_{i=1}^n \mathbf{r}_{i.}'\left(\frac{1}{\sqrt{T}}\sum_{t=1}^T \boldsymbol{\epsilon}_{.t}\right)$ which follows from (2.5) where $\mathbf{r}_{i.} = (r_{i1}, r_{i2}, \ldots, r_{in})'$ and $\boldsymbol{\epsilon}_{.t} = (\epsilon_{1,t}, \epsilon_{2,t}, \ldots, \epsilon_{n,t})'$. Then, by the CLT for weakly stationary time series and the Cramer-Wold device (see, e.g., White, 2001, Proposition 5.1), as $T \to \infty$, $\frac{1}{\sqrt{T}}\sum_{t=1}^T \mathbf{s}_n^{-1/2}\boldsymbol{\epsilon}_{.t} \xrightarrow{D} \mathbf{Z}$, where $\mathbf{s}_n = \text{diag}(\sigma_1^2, \sigma_2^2, \ldots, \sigma_n^2)$ and $\mathbf{Z} \sim N(\mathbf{0}, \boldsymbol{I}_n)$, under mutual independence of the components of $\boldsymbol{\epsilon}_{.t}$. Now the result follows from the application of the CLT for spatially correlated triangular arrays of Kelejian and Prucha (1998). Given that $\max_{1\le i\le n}\sum_{j=1}^n |r_{ij}| < \infty$, $\max_{1\le j\le n}\sum_{i=1}^n |r_{ij}| < \infty$, as

$n \to \infty$, $\frac{1}{\sqrt{n}}\mathbf{e}_n'\mathbf{R}_n\mathbf{s}_n^{1/2}\mathbf{Z} \xrightarrow{D} N(0,\sigma^2)$ where $\mathbf{e}_n$ is an n-dimensional vector of ones and $\sigma^2 = \lim_{n\to\infty}\mathbf{e}_n'\mathbf{R}_n\mathbf{s}_n\mathbf{R}_n'\mathbf{e}_n$, hence (2.13) is satisfied.

For a single cross-sectional data subject to WCD, KP proposed a spatial heteroskedasticity and autocorrelation consistent (HAC) estimator of variance-covariance matrix which can be extended to give a WCD-robust estimator of $\sigma^2_{n,T}$. Such an estimator is

$$\hat{\sigma}^2_{2,n,T} = \frac{1}{nT}\sum_{i,j=1}^{n} k_S\left(\frac{d_{ij}}{d_n}\right)\sum_{t,s=1}^{T} k_T\left(\frac{|t-s|}{l_T+1}\right)\Delta\tilde{L}_{i,t}\Delta\tilde{L}_{j,s}, \tag{2.16}$$

leading to a test statistic as

$$S^{(2)}_{n,T} = \frac{\Delta\bar{L}_{n,T}}{\hat{\sigma}_{2,n,T}/\sqrt{nT}} \xrightarrow{D} N(0,1), \tag{2.17}$$

where $d_{ij} = d_{ji} \geq 0$ denotes the distance between units i and j, and d_n the threshold distance, which is an increasing function of n such that $d_n \to \infty$ as $n \to \infty$. The estimator $\hat{\sigma}^2_{2,n,T}$ is a panel data generalization of the non-parametric covariance estimator proposed by KP. It is used by Pesaran and Tosetti (2011). Moscone and Tosetti (2012, hereafter MT) use a similar estimator with the difference being that they set $k_T(\cdot) = 1$.

Consistency of (2.16) follows from the arguments by MT. To see this define the space-time kernel by

$$k_{ST}\left(\frac{d_{ij}}{d_n}, \frac{|t-s|}{l_T+1}\right) = k_S\left(\frac{d_{ij}}{d_n}\right)k_T\left(\frac{|t-s|}{l_T+1}\right).$$

Consistency of the variance estimator require that $k_{ST}(x) : \mathbb{R} \to [0,1]$ satisfy (i) $k_{ST}(0) = 1$ and $k_{ST}(x) = 0$ for $|x| > 1$, (ii) $k_{ST}(x) = k_{ST}(-x)$, and (iii) $|k_{ST}(x) - 1| \leq C|x|^\delta$ for some $\delta \geq 1$ and $0 < C < \infty$. Then, $\hat{\sigma}^2_{2,n,T} - \sigma^2_{n,T} \xrightarrow{p} 0$ from which the asymptotic distribution for the test statistic given in (2.17) is obtained under the null hypothesis (2.6) if $\max_{1\leq i\leq n}\sum_{j=1}^{n}\mathbf{1}_{d_{ij}\leq d_n} \leq s_n$ where s_n is the number of units for which $d_{ij} \leq d_n$ and satisfies $s_n = O(n^\kappa)$ such that $0 \leq \kappa < 0.5$ and $\sum_{j=1}^{n}|\mathbf{r}_{j.}'\mathbf{r}_{i.}|d_{ij}^\eta < \infty$, $\eta \geq 1$.

In this case of WCD in addition to non-parametric estimation, one can use parametric methods to estimate the covariance matrix. When the model for the spatial dependence structure of the loss differentials is correctly specified we can expect to have more powerful tests compared to the case of non-parametric estimation.

Several other covariance estimators proposed in the literature can be obtained using the formula in (2.16). Setting $k_T(\cdot) = 1$, together with setting $k_S(\cdot) = 1$ for each $i = j$ and $k_S(\cdot) = 0$ otherwise, gives the cluster-robust estimator proposed by Arellano (1987). As explained, setting $k_T(\cdot) = 1$ and leaving $k_S(\cdot)$ unrestricted gives the estimator proposed by MT.

The case of SCD. In the case that the generating process of the loss differential series involve common factors such that there is SCD among the units, the conditions by MT are not satisfied. This case can be expressed by setting $r_{ij} = 0$ for every $i \neq j$ in (2.3) and (2.4). A CLT as in (2.13) can still be obtained under general conditions with

$$\sigma^2_{n,T} = \frac{1}{nT}\sum_{i,j=1}^{n}\sum_{t,s=1}^{T}\boldsymbol{\lambda}_i'\mathrm{E}(\mathbf{f}_t\mathbf{f}_s')\boldsymbol{\lambda}_j + \frac{1}{nT}\sum_{i=1}^{n}\sum_{t,s=1}^{T}\mathrm{E}(\varepsilon_{i,t}\varepsilon_{i,s}).$$

We write $\sqrt{nT}(\Delta\bar{L}_{n,T} - \bar{\mu}_n)$ as $\frac{1}{\sqrt{T}}\sum_{t=1}^{T}\sqrt{n}(\Delta\bar{L}_{n,t} - \bar{\mu}_n) = \frac{1}{\sqrt{T}}\sum_{t=1}^{T}\sqrt{n}\bar{v}_{n,t}$ where $\bar{L}_{n,t} = \frac{1}{n}\sum_{i=1}^{n}\Delta L_{i,t}$ and $\bar{v}_{n,t} = \frac{1}{n}\sum_{i=1}^{n} v_{i,t}$. Suppose that $v_{i,t}$ is α-mixing of size $r/(r-1)$ with $r > 1$ as defined by Driscoll and Kraay (1998). This implies that $\bar{v}_{n,t}$ is α-mixing of size $r/(r-1)$ as well. If $\mathrm{E}|\bar{v}_{n,t}|^r < \delta < \infty$ for some $r \geq 2$ and $\bar{\sigma}^2_{n,T} = \mathrm{Var}[T^{-1/2}\sum_{t=1}^{T}\bar{v}_{n,t}] > \delta > 0$ the CLT for dependent and heterogeneously distributed random variables (see, e.g., White, 2001, Theorem 5.20) can be applied such that $\sqrt{T}\bar{v}_{n,T}/\bar{\sigma}_{n,T} \sim N(0,1)$ for all T sufficiently large from which the result in (2.13) follows.

In this case, the variance estimator given in (2.16) can be modified by setting $k_S(\cdot) = 1$ and leaving $k_T(\cdot)$ unrestricted. This variance estimator does not require any knowledge of a distance measure between the units. Moreover, it assigns weights equal to one for all covariances, hence robust to SCD as well as WCD. The test statistic takes the form:

$$S^{(3)}_{n,T} = \frac{\Delta\bar{L}_{n,T}}{\hat{\sigma}_{3,n,T}/\sqrt{nT}} \xrightarrow{D} N(0,1), \tag{2.18}$$

where

$$\hat{\sigma}^2_{3,n,T} = \frac{1}{nT}\sum_{i,j=1}^{n}\sum_{t,s=1}^{T} k_T\left(\frac{|t-s|}{l_T+1}\right)\Delta\tilde{L}_{i,t}\Delta\tilde{L}_{j,s}. \tag{2.19}$$

The variance estimator (2.19) was proposed by Driscoll and Kraay (1998), which is valid when T is large, regardless of n finite or infinite. Consistency of the estimator follows immediately from the conditions given above except that now it is required $v_{i,t}$ to be α-mixing of size $2r/(r-1)$ with $r > 1$ and the factor loadings $\boldsymbol{\lambda}_i$ to be uniformly bounded. Then the null distribution in (2.18) follows.

It is known that when the number of units in the panel is close to the number of time series observations this estimator performs poorly. An alternative way to estimate the covariance matrix is to exploit the factor structure of the DGP. The PC estimation of the factor model defined by (2.3)-(2.5) is investigated by Stock and Watson (2002), Bai and Ng (2002), Bai (2003), among others. This method minimizes the sum of squared residuals $SSR = (nT)^{-1}\sum_{i=1}^{n}\sum_{t=1}^{T}(\Delta\tilde{L}_{i,t} - \boldsymbol{\lambda}_i'\mathbf{f}_t)^2$ subject to $\mathrm{Var}(\mathbf{f}_t) = \boldsymbol{I}_m$. Then the solution for the estimates of the common factors, $\widehat{\mathbf{f}}_t$, are given by $\sqrt{T}$ times the first m eigenvectors of the matrix $\sum_{i=1}^{n}\boldsymbol{\Delta}\mathbf{L}_{i.}\boldsymbol{\Delta}\mathbf{L}_{i.}'$ with $\boldsymbol{\Delta}\mathbf{L}_{i.} = (\Delta L_{i,1}, \Delta L_{i,2}, \ldots, \Delta L_{i,T})'$ and the factor loadings can be estimated as $\widehat{\boldsymbol{\lambda}}_i = \frac{1}{T}\sum_{t=1}^{T}\widehat{\mathbf{f}}_t\Delta\tilde{L}_{i,t}$. Then the overall EPA hypothesis can be tested using

$$S_{n,T}^{(4)} = \frac{\Delta\bar{L}_{n,T}}{\hat{\sigma}_{4,n,T}/\sqrt{nT}} \xrightarrow{D} N(0,1), \tag{2.20}$$

where

$$\hat{\sigma}_{4,n,T}^2 = \frac{1}{nT}\sum_{i,j=1}^{n}\sum_{t,s=1}^{T}k_T\left(\frac{|t-s|}{l_T+1}\right)\widehat{\boldsymbol{\lambda}}_i'\widehat{\mathbf{f}}_t\widehat{\mathbf{f}}_s'\widehat{\boldsymbol{\lambda}}_j + \frac{1}{nT}\sum_{i=1}^{n}\sum_{t,s=1}^{T}k_T\left(\frac{|t-s|}{l_T+1}\right)\widehat{\varepsilon}_{i,t}\widehat{\varepsilon}_{i,s} \tag{2.21}$$

with $\widehat{\varepsilon}_{i,t} = \Delta\tilde{L}_{i,t} - \widehat{\boldsymbol{\lambda}}_i'\widehat{\mathbf{f}}_t$. The conditions under which the estimates $\widehat{\boldsymbol{\lambda}}_i'$ and $\widehat{\mathbf{f}}_t$ are consistent are given in Bai and Ng (2002). Consistency of the variance estimator (2.21) follows directly under these conditions together with the conditions on consistent estimation of the long-run variance as in Andrews (1991). These lead to the null distribution given in (2.20).

The case of both SCD and WCD. This is the most general case of the model defined by (2.3)-(2.5) with no specific restriction imposed on the parameters. Under the α-mixing conditions discussed previously, the CLT in (2.13) still holds with

$$\sigma_{n,T}^2 = \frac{1}{nT}\sum_{i,j=1}^{n}\sum_{t,s=1}^{T}\boldsymbol{\lambda}_i'\mathrm{E}(\mathbf{f}_t\mathbf{f}_s')\boldsymbol{\lambda}_j + \frac{1}{nT}\sum_{i,j=1}^{n}\sum_{t,s=1}^{T}\mathbf{r}_{i.}'\boldsymbol{\gamma}_{\epsilon_i}(|t-s|)\mathbf{r}_{j.}.$$

The test (2.20) is robust to SCD because of the presence of common factors. However, it is obtained under the assumption that the residuals do not contain WCD. Under the conditions discussed previously, the test (2.18) is robust to the presence of both SCD and WCD but as mentioned, performs poorly when n is close to T. Another test can be obtained by using the kernel methods. We have

$$S_{n,T}^{(5)} = \frac{\Delta \bar{L}_{n,T}}{\hat{\sigma}_{5,n,T}/\sqrt{nT}} \xrightarrow{D} N(0,1), \tag{2.22}$$

where

$$\hat{\sigma}_{5,n,T}^2 = \frac{1}{nT}\sum_{i,j=1}^{n}\sum_{t,s=1}^{T} k_T\left(\frac{|t-s|}{l_T+1}\right)\widehat{\boldsymbol{\lambda}}_i'\widehat{\mathbf{f}}_t\widehat{\mathbf{f}}_s'\widehat{\boldsymbol{\lambda}}_j + \frac{1}{nT}\sum_{i,j=1}^{n} k_S\left(\frac{d_{ij}}{d_n}\right)\sum_{t,s=1}^{T} k_T\left(\frac{|t-s|}{l_T+1}\right)\widehat{\varepsilon}_{i,t}\widehat{\varepsilon}_{i,s}. \tag{2.23}$$

2.3.2 Tests for Joint Equal Predictive Ability

In this section we are concerned with testing the hypothesis (2.7), i.e., $H_0 : \mu_1 = \mu_2 = \cdots = \mu_n = 0$. The discussion is first based on large T and small n scenario. In the case of fixed n, by the CLT for weakly stationary time series and the Cramer-Wold device, the joint limiting distribution of the vector of loss differential series $\boldsymbol{\Delta}\bar{\mathbf{L}}_T = (\Delta\bar{L}_{1,T}, \Delta\bar{L}_{2,T}, \ldots, \Delta\bar{L}_{n,T})'$ is given by

$$\sqrt{T}\boldsymbol{\Omega}_n^{1/2}(\boldsymbol{\Delta}\bar{\mathbf{L}}_T - \boldsymbol{\mu}) \xrightarrow{D} N(\mathbf{0}, \boldsymbol{I}_n), \tag{2.24}$$

as $T \to \infty$, where $\boldsymbol{\mu} = (\mu_1, \mu_2, \ldots, \mu_n)'$,

$$\boldsymbol{\Omega}_n = \frac{1}{T}\sum_{i,j=1}^{n}\sum_{t,s=1}^{T} \boldsymbol{h}_i\boldsymbol{h}_j'\mathrm{E}(v_{i,t}v_{j,s}),$$

with $\boldsymbol{h}_i$ being the ith column of $\boldsymbol{I}_n$.

The case of no CD. Under cross-sectional independence of the loss differential series, we have $\boldsymbol{\Omega}_n = \mathrm{diag}(\sigma_1^2, \sigma_2^2, \ldots, \sigma_n^2)$ with σ_i^2 being defined in (2.9). Therefore, the first test statistic considered is

$$J_{n,T}^{(1)} = T\boldsymbol{\Delta}\bar{\mathbf{L}}_T'\widehat{\boldsymbol{\Omega}}_{1,n}^{-1}\boldsymbol{\Delta}\bar{\mathbf{L}}_T \xrightarrow{D} \chi_n^2, \tag{2.25}$$

where $\widehat{\boldsymbol{\Omega}}_{1,n}$ is a consistent estimator of $\boldsymbol{\Omega}_n$ with diagonal elements $\hat{\sigma}_{i,T}^2$ given in (2.15).

Consistency of the estimator $\widehat{\mathbf{\Omega}}_{1,n}$ follows directly from the fact that its components are consistent under the conditions, for instance, given by Andrews (1991). Hence, this test statistic is robust against arbitrary time dependence as is $S_{n,T}^{(1)}$.

The case of WCD. When the panel data exhibit WCD, $\mathbf{\Omega}_n$ is no longer diagonal. In the case of small n, the panel generalization of the non-parametric variance estimator of KP is not appropriate. In this case, Driscoll and Kraay (1998) estimator can be used as explained in the case of SCD given below. In the case of large n, we can still use the non-parametric estimator. A natural extension of $S_{n,T}^{(2)}$ gives the second test statistic that is robust to arbitrary time and cross sectional dependence:

$$J_{n,T}^{(2)} = T\mathbf{\Delta}\bar{\mathbf{L}}_T'\widehat{\mathbf{\Omega}}_{2,n}^{-1}\mathbf{\Delta}\bar{\mathbf{L}}_T \xrightarrow{D} \chi_n^2, \tag{2.26}$$

where

$$\widehat{\mathbf{\Omega}}_{2,n} = \frac{1}{T}\sum_{i,j=1}^{n} k_S\left(\frac{d_{ij}}{d_n}\right)\sum_{t,s=1}^{T} k_T\left(\frac{|t-s|}{l_T+1}\right)\boldsymbol{h}_i\boldsymbol{h}_j'\Delta\tilde{L}_{i,t}\Delta\tilde{L}_{j,s}, \tag{2.27}$$

with $\boldsymbol{h}_i$ being the ith column of $\boldsymbol{I}_n$.

The null distribution stated in (2.26) is not obvious as the consistency of the non-parametric variance estimator (2.27) requires large n but the test statistic has infinite variance as $n \to \infty$. Alternatively, one can use a centered and scaled version of this statistic which is asymptotically normal. This is explained below.

The case of SCD. When the loss differentials are subject to SCD, similar to the steps leading to the overall EPA test $S_{n,T}^{(3)}$, we modify the covariance estimator (2.27) by imposing $k_S(d_{ij}/d_n) = 1$, so that a known distance measure is not required. The test statistic is given by

$$J_{n,T}^{(3)} = T\mathbf{\Delta}\bar{\mathbf{L}}_T'\widehat{\mathbf{\Omega}}_{3,n}^{-1}\mathbf{\Delta}\bar{\mathbf{L}}_T \xrightarrow{D} \chi_n^2, \tag{2.28}$$

where

$$\widehat{\mathbf{\Omega}}_{3,n} = \frac{1}{T}\sum_{i,j=1}^{n}\sum_{t,s=1}^{T} k_T\left(\frac{|t-s|}{l_T+1}\right)\boldsymbol{h}_i\boldsymbol{h}_j'\Delta\tilde{L}_{i,t}\Delta\tilde{L}_{j,s}. \tag{2.29}$$

Although there is an advantage of using this estimator in the sense that it is robust in the case of SCD, WCD or both and it does not require a known distance measure, it has an important disadvantage. It is not of full rank even if the population variance-covariance matrix is so. Namely, rank($\widehat{\mathbf{\Omega}}_{3,n}$) is at most T, therefore, it is not invertible whenever $n > T$. This difficulty can be overcome by using the PC estimates of the factors and their loadings, leading to a new joint EPA test statistic as

$$J_{n,T}^{(4)} = T\mathbf{\Delta}\bar{\mathbf{L}}_T'\widehat{\mathbf{\Omega}}_{4,n}^{-1}\mathbf{\Delta}\bar{\mathbf{L}}_T \xrightarrow{D} \chi_n^2, \tag{2.30}$$

where

$$\widehat{\mathbf{\Omega}}_{4,n} = \widehat{\mathbf{\Lambda}}\left[\frac{1}{T}\sum_{t,s=1}^{T} k_T\left(\frac{|t-s|}{l_T+1}\right)\widehat{\mathbf{f}}_t\widehat{\mathbf{f}}_s'\right]\widehat{\mathbf{\Lambda}}' + \widehat{\mathbf{\Sigma}}_{1,n}, \tag{2.31}$$

and

$$\widehat{\mathbf{\Sigma}}_{1,n} = \frac{1}{T}\sum_{i=1}^{n}\sum_{t,s=1}^{T} k_T\left(\frac{|t-s|}{l_T+1}\right)\mathrm{diag}(\boldsymbol{h}_i)\widehat{\varepsilon}_{i,t}\widehat{\varepsilon}_{i,s}, \tag{2.32}$$

with $\widehat{\mathbf{\Lambda}} = (\widehat{\boldsymbol{\lambda}}_1, \widehat{\boldsymbol{\lambda}}_2, \ldots, \widehat{\boldsymbol{\lambda}}_n)'$.

Once more the null distribution stated in (2.30) is not obvious because PC estimates of the common factors require large n but the test statistic has infinite variance as $n \to \infty$. Again, one can use a centered and scaled version of this statistic which is asymptotically normal which is explained below.

The case of both SCD and WCD. As in the previous section, a joint test statistic which is robust to both common factors and spatial dependence can be obtained as

$$J_{n,T}^{(5)} = T\mathbf{\Delta}\bar{\mathbf{L}}_T'\widehat{\mathbf{\Omega}}_{5,n}^{-1}\mathbf{\Delta}\bar{\mathbf{L}}_T \xrightarrow{D} \chi_n^2, \tag{2.33}$$

where

$$\widehat{\mathbf{\Omega}}_{5,n} = \widehat{\mathbf{\Lambda}}\left[\frac{1}{T}\sum_{t,s=1}^{T} k_T\left(\frac{|t-s|}{l_T+1}\right)\widehat{\mathbf{f}}_t\widehat{\mathbf{f}}_s'\right]\widehat{\mathbf{\Lambda}}' + \widehat{\mathbf{\Sigma}}_{2,n}, \tag{2.34}$$

and

$$\widehat{\mathbf{\Sigma}}_{2,n} = \frac{1}{T}\sum_{i,j=1}^{n} k_S\left(\frac{d_{ij}}{d_n}\right)\sum_{t,s=1}^{T} k_T\left(\frac{|t-s|}{l_T+1}\right)\boldsymbol{h}_i\boldsymbol{h}_j'\widehat{\varepsilon}_{i,t}\widehat{\varepsilon}_{j,s}. \tag{2.35}$$

Below, a centered and scaled version of this test statistic is proposed.

Standardized test statistics. When n grows with T, it is clear that the limiting chi-square distribution is not meaningful and in this case a standardized chi-square test can be used. For the tests given above, these standardized statistics are

$$Z_{n,T}^{(g)} = \frac{J_{n,T}^{(g)} - n}{\sqrt{2n}} \xrightarrow{D} N(0,1), \quad g = 1, \ldots, 5, \tag{2.36}$$

where the stated asymptotic standard normal distribution holds under the particular assumption of each statistics $J_{n,T}^{(g)}$, $g = 1, \ldots, 5$.

2.4 Monte Carlo Study

To investigate the small sample properties of the test statistics given above, a set of Monte Carlo simulations are conducted. 2000 samples from each DGP described below for the dimensions of $T \in \{10, 20, 30, 50, 100\}$, $n \in \{10, 20, 30, 50, 100, 200\}$ are generated. All tests are applied for two nominal size values, 1% and 5%.

2.4.1 Design of the Experiments

Two different DGPs are considered to explore the effect of WCD and SCD on the performance of the tests. DGP1 contains only spatial dependence. In this case, for each of the cross-sections or units ($i = 1, 2, \ldots, n$), two independent forecast error series ($e_{1i,t}, e_{2i,t}$) are generated using two spatial AR(1) processes defined as

$$\zeta_{l,it} = \rho \sum_{j=1}^{n} w_{ij} \zeta_{l,jt} + u_{l,it}, \quad \text{where,} \quad u_{l,it} \sim N(0,1), \quad l = 1, 2, \tag{2.37}$$

where w_{ij} is the element of the spatial matrix $\mathbf{W}_n$ in row i and column j. A rook-type spatial weight matrix is used. To make the power results across different levels of spatial dependence comparable, the unconditional variance of the forecast error series $e_{l,it}$, $l = 1, 2$, is held fixed for each panel. To generate such series we proceed as follows: First the spatial AR(1) processes is written in matrix form as

$$\boldsymbol{\zeta}_{l,.t} = \mathbf{S}_n \mathbf{u}_{l,.t}, \tag{2.38}$$

where $\boldsymbol{\zeta}_{l,.t} = (\zeta_{l,1t}, \zeta_{l,2t}, \ldots, \zeta_{l,nt})'$, $\mathbf{u}_{l,.t} = (\mathbf{u}_{l,1t}, \mathbf{u}_{l,2t}, \ldots, \mathbf{u}_{l,nt})'$, $\mathbf{S}_n = (\boldsymbol{I}_n - \rho \mathbf{W}_n)^{-1}$. Then, the forecast error series are generated according to

$$\mathbf{e}_{l,.t} = \mathbf{P}_n \boldsymbol{\zeta}_{l,.t}, \tag{2.39}$$

where $\mathbf{e}_{l,.t} = (e_{l,1t}, e_{l,2t}, \ldots, e_{l,nt})'$ and $\mathbf{P}_n$ has elements $p_{ij} = \sqrt{1/s_{2,ij}}$ if $i = j$ and zeros otherwise, with $s_{2,ij}$ being the i,j-th element of $\mathbf{S}_n\mathbf{S}_n'$. It can now be shown that all diagonal elements of the matrix $\mathbf{P}_n\mathbf{S}_n\mathbf{S}_n'\mathbf{P}_n'$ equal to 1.

Three different spatial AR(1) parameters are considered: $\rho = 0$, 0.5 and 0.9, which are selected to represent no spatial dependence, low spatial dependence and high spatial dependence cases, respectively. As error series are generated for each unit as white noises, it is implicitly assumed that these are one-step ahead forecasts. In the computation of the test statistics, it is assumed that this is correctly specified. Hence, in the computation of the long-run variances, covariances through time are not taken into account. In this DGP a quadratic loss function is used.

DGP2 contains common factors as well as spatial dependence. In this case, following GW we directly generate the loss differential, hence we do not rely on a specific loss function. This is given by

$$\Delta L_{i,t} = \phi(\mu_i + \lambda_{1i} f_{1t} + \lambda_{2i} f_{2t} + \varepsilon_{i,t}). \tag{2.40}$$

To investigate the size properties we set $\mu_i = 0$ for each $i = 1, 2, \ldots, n$ and generate factor loadings as

$$\lambda_{1i}, \lambda_{2i} \sim N(1, 0.2). \tag{2.41}$$

The common factors are formed by

$$f_{1t}, f_{2t} \sim N(0, 1), \tag{2.42}$$

hence, they do not incorporate autocorrelation. The error series $\varepsilon_{i,t}$ are generated in the same spirit as in (2.39). Hence, we have 3 cases for DGP2 also, namely no spatial dependence, low spatial dependence and high spatial dependence. We finally set $\phi = 1/3.4$ to control for the variance of the loss differential series.

We explore the power properties of various tests under two different alternative hypothesis. The first one is the homogeneous alternative and the second one is the heterogeneous alternative. For DGP1 with homogeneous alternative, we generate a third set of forecast error series as $e_{3i,t} = \sqrt{1.2}e_{2i,t}$ and report the results from testing the equality of forecast accuracy of $e_{1i,t}$ and $e_{3i,t}$. In the heterogeneous scenario, we generate the third series according to $e_{3i,t} = \sqrt{\theta_i}e_{2i,t}$ where

$$\theta_i \sim U(0.6, 1.4). \tag{2.43}$$

Similarly, in the case of DGP2, we set $\mu_i = 1.2$ for each $i = 1, 2, \dots, n$ in the case of homogeneous alternative and

$$\mu_i \sim U(-0.4, 0.4), \tag{2.44}$$

in the case of heterogeneous alternative. It is important to note that in the case of heterogeneous alternative, the unconditional expectations of the loss differentials are equal to zero in all DGPs. Hence, the overall EPA hypothesis holds. On the other hand, for each unit, the expected value of the loss differential is different from zero. Therefore, the joint EPA hypothesis does not hold. As a consequence, we expect the overall EPA tests not to have increasing power against the heterogeneous alternative whereas joint EPA tests to be consistent.

As we generate one-step ahead forecasts, the time series kernel $k_T(\cdot) = 1$ if $t = s$ and $k_T(\cdot) = 0$ otherwise. Spatial interactions between units are created with a rook-type weight matrix where two units in the panel are neighbors if their Euclidean distance is less than or equal to one. In the computation of the spatial kernel $k_S(\cdot)$, we used these distances and we implemented several different kernel functions used frequently in time series literature. These are truncated, Bartlett, Parzen, Tukey and Quadratic Spectral. Following KP, we set the spatial kernel bandwidth to $\lfloor n^{1/4} \rfloor$.

For the tests $S^{(2)}_{n,T}$ and $J^{(2)}_{n,T}$, the results from all these kernels are reported. For $S^{(4)}_{n,T}$ and $J^{(4)}_{n,T}$ we consider different possibilities concerning the number of common factors. First, we consider extracting 2 common factors from the panel which is the correct number of factors in DGP2. Second, we consider the possibility of a number of common factors which expands with the number of units in the panel. As shown by Sarafidis and Wansbeek (2012), all common spatial processes can be written in the form of a factor model of factor dimension

n. Hence, it is interesting to see if choosing a number of common factors growing with the number of units will help to deal with spatial dependence. For these tests, we chose the number of common factors as $\lfloor n^{1/4} \rfloor$. We implement the tests $S_{n,T}^{(5)}$ and $J_{n,T}^{(5)}$ only with Bartlett kernel.

2.4.2 Results

The results of the Monte Carlo experiments are discussed in the following subsections. Size properties are summarized in Section 2.4.2.1 and size adjusted power results are in Section 2.4.2.2. The comments focus on size and size adjusted power in the case of low spatial dependence. These results are given in Appendix 2.A. The power properties of the EPA tests for all data generating processes and cases, size and size adjusted power results for the cases of no spatial dependence and high spatial dependence can be found in Appendix B.

2.4.2.1 Size Properties

Main Results. The results on the size properties of tests with DGP1 under low spatial dependence are given in Table 2.7. As expected, the non-robust test $S_{n,T}^{(1)}$ has size distortions which do not disappear with increases in the sample size. For the smallest samples with $T = 10$ and $n = 10$, this particular setting provides an empirical size of 3.65% and 12.35% for 1% and 5% nominal levels for the test, respectively. The kernel robust test $S_{n,T}^{(2)}$ greatly improves the size properties over the non-robust test even with the smallest samples. The truncated kernel performs the best with small n. For instance, when $n = 20$ and $T = 30$, the empirical size of the test with truncated and Bartlett kernels are 1.65% and 2.9% for 1% nominal level, respectively. In this case Parzen kernel appears to be the least liable choice. The performance of the cluster-robust test improves with T but in small samples it does not overperform the non-robust test strongly. Whenever we have $T \geq 50$ it is nearly correctly sized. Factor robust tests $S_{n,T}^{(4)}$ and $S_{n,T}^{(5)}$ are undersized when $T = 10$ for the nominal level 1%. However, they are performing very well to correct for spatial dependence for larger sample sizes.

Typically, the performance of the joint EPA tests falls with n and improves with T. In the case of joint tests $J_{n,T}^{(2)}$, truncated kernel is not found to be the best performance option anymore for small n. In this case Parzen kernel looks like the most liable alternative. Interestingly, the performance of the test does not fall quickly with n for a large but fixed T, in the cases of Bartlett, Parzen and Tukey kernels. For instance, when $T = 100$ and $n = 200$ the empirical sizes of these tests are 3.55%, 2.10% and 3.80% for 1% nominal level, respectively. For quadratic spectral kernel this number is 7.7%. The performance of factor robust tests $J_{n,T}^{(4)}$ and $J_{n,T}^{(5)}$ are most satisfying, as before. One exception is the $J_{n,T}^{(5)}$ in large n and moderate T cases.

As we expect the conclusions change dramatically in the case of DGP2 for which the results are given in Table 2.8. In this case all overall EPA tests which do not take common factors in account are grossly over-sized. As in the previous cases the cluster-robust test $S_{n,T}^{(3)}$ performs well when T is large and n is small. $S_{n,T}^{(4)}$ and $S_{n,T}^{(5)}$ are even more undersized in this setting for small T. However, they are correctly sized for moderate to large T.

In the case of joint tests the kernel robust test $S_{n,T}^{(2)}$ has an improving performance for fixed n and growing T. It reaches the correct size especially with the Bartlett and quadratic spectral kernels. Among the factor robust tests $J_{n,T}^{(4)}$ looks like the better choice. This is interesting as $J_{n,T}^{(5)}$ is robust to both WCD and SCD while $J_{n,T}^{(4)}$ controls only the SCD.

Additional Findings. The results are broadly confirmed in the cases of no spatial dependence and high spatial dependence. The results on the size properties of tests with DGP1 with no spatial dependence are given in Table B1 whereas the results for high spatial dependence are in Table B2. The corresponding results in the case of DGP2 are reported in Tables B3 and B4, respectively.

When there is no spatial dependence in the generating process of the loss differentials, the non-robust overall test $S_{n,T}^{(1)}$ is correctly sized, as expected. Most of the kernel robust tests also have size close to the nominal values with the exception of $S_{n,T}^{(2)}$ with truncated kernel. In moderate values of n, this test is over-sized. As before, joint tests show serious size distortions as n increases, but their properties improve as T increases. Importantly, this problem is much less serious in the case of factor-robust joint tests. They have much better size properties even when n is large. For instance, in 1% nominal level, $J_{n,T}^{(4)}$ with a fixed number of common factor has a size equal to 10.15% when $n = 200$ and $T = 10$. The corresponding value for the non-robust joint test $J^{(1)}_{n,T}$ is 74.35%.

In the case of high spatial dependence the size properties of most of the tests are deteriorated. The kernel-robust overall tests are correcting the spatial dependence but even in largest samples they show size distortions. One exception is the test with truncated kernel which is much less over-sized for large values of n. In 1% nominal level, when $n, T = 100$ its size is equal to 1.75%. Confirming a general behavior, the factor-robust overall tests are mostly under-sized in small samples, but they are performing better than kernel-robust tests most of the times. The best performing test in this case is $S^{(3)}_{n,T}$ which has good size as long as $T \geq 30$. Moreover, its performance does not depend on the number of cross-sectional units. Finally, the conclusions made for the joint tests in the case of low spatial dependence are valid here too, with the exception that they do not perform perfectly even in very large samples.

2.4.2.2 Power and Size Adjusted Power Properties

Main Results. The size adjusted power results of the tests for the homogeneous alternative hypothesis are given in Tables 2.9 and 2.10, whereas the results for heterogeneous alternative are given in Tables 2.11 and 2.12.

Table 2.9 reports the results for DGP1 with low spatial dependence. In this case all overall EPA tests have satisfactory power even with small samples. The results show that the kernel-robust tests $S^{(2)}_{n,T}$ do not improve the size adjusted power over the non-robust test $S^{(1)}_{n,T}$. The differences are very small and even there are cases of non-robust having better performance over the robust tests. For instance, for the smallest samples where $T = 10$ and $n = 10$, $S^{(2)}_{n,T}$ with truncated kernel has a size adjusted power of 11.65% in 5% nominal level whereas this number equals to 10.9% for $S^{(1)}_{n,T}$. When $n \geq 50$, $S^{(1)}_{n,T}$ outperforms the robust test. An important result in this experiment is that the size adjusted power of all overall EPA tests are increasing with either n or T.

This is not the case for joint EPA tests. In small samples, size adjusted power for the joint EPA tests are lower and they increase only in the dimension of T. For the test $J^{(1)}_{n,T}$ when $T = 10$ and $n = 10$ the size adjusted power is as low as 1.3% and 6.3% for 1% and

5% nominal levels, respectively. As before, the size adjusted power of the CD robust tests are lower but the differences are not big.

Table 2.10 gives the results on the case of common factors, that is DGP2 with low spatial dependence. As in this case we found that the non-robust tests $S_{n,T}^{(1)}$ and $S_{n,T}^{(2)}$ are highly over-sized we focus on the rest of the results. An interesting result in this case is that the size adjusted power of the robust overall tests do not increase with n. All tests have similar performance, including the cluster-robust test $S_{n,T}^{(3)}$ which has slightly smaller size adjusted power in small samples. As T increases it quickly reaches the level of other robust tests $S_{n,T}^{(4)}$ and $S_{n,T}^{(5)}$.

The results for the joint EPA tests are similar such that the size adjusted power of the tests increase only with T. In small samples it is very low. For instance, when $T = 10$ and $n = 200$, $J_{n,T}^{(4)}$ with a fixed number of common factors has a size adjusted power of 6.2% and 9.1% for 1% and 5% nominal levels, respectively. However, the size adjusted power of the test rises quickly as T increases.

Table 2.11 reports the results under the heterogeneous alternative hypothesis in the absence of SCD. This is an interesting case where we expect no improvement in the size adjusted power properties of the overall EPA tests $S_{n,T}^{(1)}$-$S_{n,T}^{(5)}$. The results confirm this expectation. For instance, in the extreme case of $T = 100$ and $n = 200$, the size adjusted power of the tests $S_{n,T}^{(1)}$ and $S_{n,T}^{(2)}$ with truncated kernel are 3.50% and 4.05% for 1% nominal level, respectively.

The performance of the joint EPA tests improve with the increase in T. For instance, for $n = 50$ the size adjusted power of the test $J_{n,T}^{(2)}$ with truncated kernel increase from 13.25% while $T = 50$ to 44.95% while $T = 100$ in 5% nominal level. The factor robust tests have similar size adjusted power in general. The corresponding numbers for the test $J_{n,T}^{(4)}$ with a fixed number of common factors are 14.70% while $T = 50$ to 43.25%.

The results for the case of heterogeneous alternative hypothesis with DGP2 and low spatial dependence are given in Table 2.12. As in the previous case the size adjusted power of overall EPA tests do not improve with the increases in sample size. In this case differences between robust tests and non-robust test $J_{n,T}^{(1)}$ is pronounced. There is nearly no improvement in the size adjusted power of the latter. In the extreme case of $T = 100$

and $n = 200$, the size adjusted power of the tests $J^{(1)}_{n,T}$ is 1.75% and 8.55% for 1% and 5% nominal levels, respectively. This result is similar for the kernel-robust test with truncated kernel. Whereas, for Bartlett, Tukey and quadratic spectral kernels we have good power properties for large n and large T. In this case an important difference is observed between the kernel robust tests $J^{(2)}_{n,T}$ and factor robust tests $J^{(4)}_{n,T}$ and $J^{(5)}_{n,T}$ such that the size adjusted power of the latter ones improve with T for a fixed n.

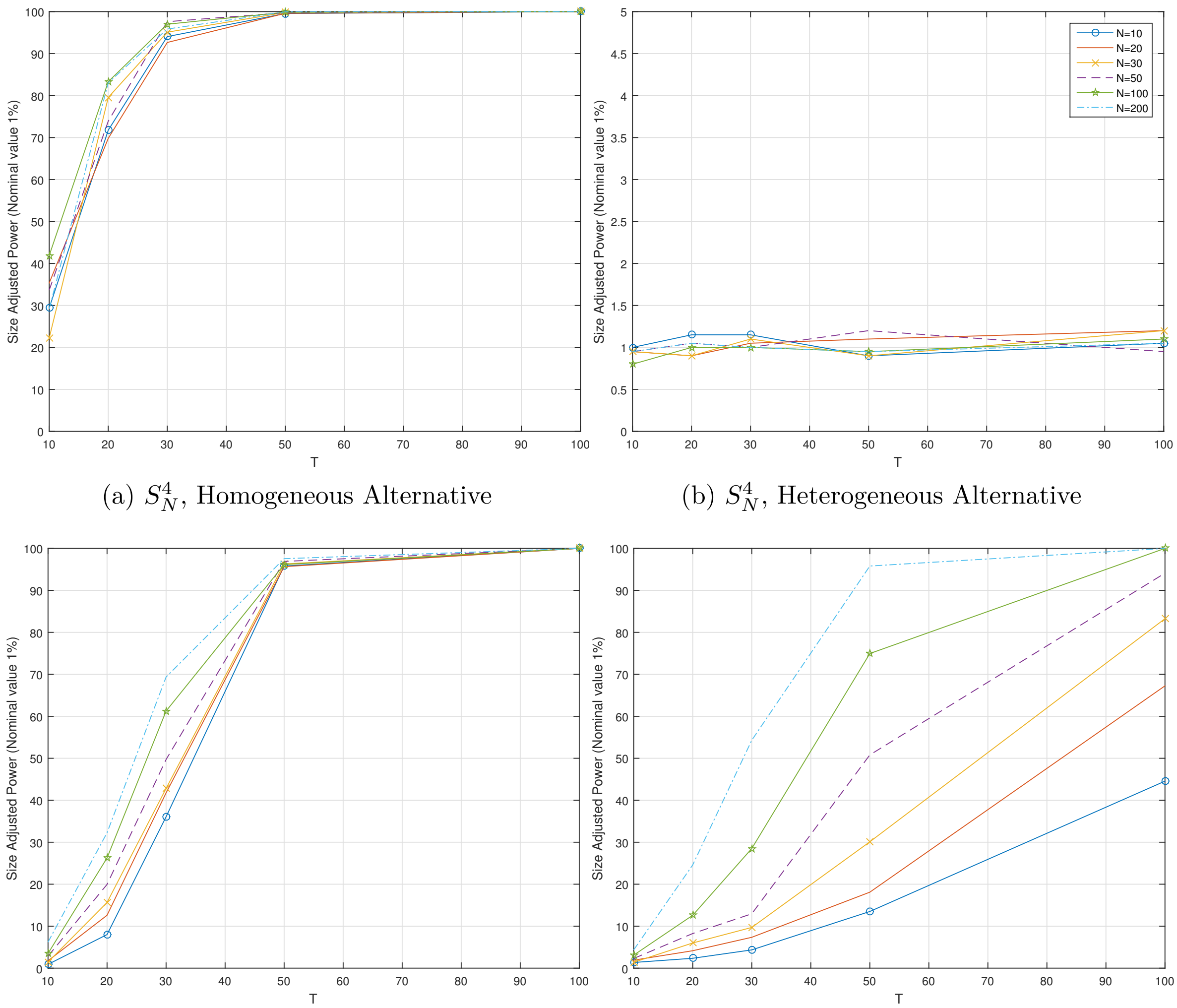
The size adjusted power properties of the factor robust tests $S^{(4)}_{n,T}$ and $J^{(4)}_{n,T}$ are also shown in Figure 2.2 for the case of DGP2 and low spatial dependence. It is clearly seen that under the homogeneous alternative hypothesis the size adjusted power of the overall test $S^{(4)}_{n,T}$ is higher than the joint test $J^{(4)}_{n,T}$ for all sample sizes. However, under the heterogeneous alternative the size adjusted power of the overall test equals to the nominal value 1% for any sample size.

Additional Findings. The power and size adjusted power in the case of no spatial dependence robust and non-robust tests can be summarized as follows: the power and size adjusted power of the non-robust tests are higher than the robust tests under no spatial dependence in DGP1 (Tables B5 and B17). However, when there is high spatial dependence the above results become much more pronounced such that the non-robust test performs very poorly as it is over-sized (Tables B7 and B18). In the case of DGP2 the factor robust tests perform well in moderate to large samples (Tables B8-B10 and Tables B19-B20). The results in the case of heterogeneous alternative confirm the previous findings (Tables B11-B16 and Tables B21-B24).

2.5 Empirical Application

2.5.1 Data, Empirical Setup And Preliminaries

In this section, we use the tests proposed to compare the OECD and IMF GDP growth forecasts. The data for the IMF forecast errors come from their Historical WEO Forecasts Database. The database includes historical τ-steps ahead forecast values, $\tau = 1, 2, \ldots, 5$, for GDP growth rate. The data covers up to 192 countries and starts from early 1990s. We



(a) S_N^4, Homogeneous Alternative

(b) S_N^4, Heterogeneous Alternative

(c) J_N^4, Homogeneous Alternative

(d) J_N^4, Heterogeneous Alternative

Figure 2.2: Size Adjusted Power of Factor-Robust Tests Under Different Alternative Hypotheses for DGP2 and Low Spatial Dependence

collected similar data from the past vintages of the Economic Outlook of the OECD. The Economic Outlook contains only 1-step ahead forecasts. Eventually we have a balanced panel dataset of GDP growth forecast errors of 29 OECD countries from the two organization between 1998 and 2016. To investigate the role of heterogeneity and the change in the dimensions of the panel dataset, we also apply the tests to a sample of G7 countries between 1991 and 2016. This dataset comes from Turner (2017).

We implement the tests described above on the two datasets. We create four different loss series: absolute loss, quadratic loss and two different types of linex loss. The absolute error loss differential is created as

$$\Delta L^1_{i,t} = |e_{1i,t}| - |e_{2i,t}|,$$

where, as is throughout the application, first organization is the OECD. This loss function is important when we compare the magnitude of the (absolute) bias made by the two organizations. The quadratic loss is generated as

$$\Delta L^2_{i,t} = e^2_{1i,t} - e^2_{2i,t}.$$

This loss function is arguably the most frequently used one and it is useful to compare the variance in the forecast errors. For instance, if the forecasts of the both organizations are unbiased the expectation of absolute error loss is zero and quadratic loss permits to compare the variances directly.

The disadvantage of these two loss functions is that they give equal weight to positive and negative forecast errors. A more flexible loss function is linex loss where it is possible to choose a parameter to give higher weight to either depending on their economic importance. In Section 2.1, we saw that the forecast errors of the two organizations take very large negative values for all countries during the financial crisis. Hence, to compare the performance of the two organizations during the crisis one can give more weight to negative values, vice versa. The two linex loss differential series we use are computed as

$$\Delta L^3_{i,t} = \left(\exp\{\rho_1 e_{1i,t}\} - \rho_1 e_{1i,t} - 1\right) - \left(\exp\{\rho_1 e_{2i,t}\} - \rho_1 e_{2i,t} - 1\right),$$

$$\Delta L^4_{i,t} = \left(\exp\{\rho_2 e_{1i,t}\} - \rho_2 e_{1i,t} - 1\right) - \left(\exp\{\rho_2 e_{2i,t}\} - \rho_2 e_{2i,t} - 1\right),$$

where $\rho_1 = -0.35$ and $\rho_1 = 0.5$. With the first choice of the parameter more weight is given to negative values whereas with the second more weight is given to positive values. Thus, the first function can be used to compare the performance during crisis period.

We begin the analysis by the DM tests applied to each country. We compute the DM test statistic for each country between the years 1998 and 2016 using all four loss functions. In the computations, we use a Bartlett kernel with a bandwidth parameter of 0 because we have 1-step ahead forecasts. The result are given in Table 2.2.

First, in terms of the sign of the statistics, a considerable amount of heterogeneity can be observed in the sample. For all types of loss functions roughly half of the statistics are negative. Second, most of these statistics are statistically insignificant with exceptions being BEL, CAN, ESP, HUN, LUX and NZL. For BEL which is a country where the predictive ability of the IMF is superior, the EPA hypothesis can be rejected at 5% and 10% levels with absolute and quadratic losses, respectively. In the case of CAN, we can reject the EPA hypothesis with absolute loss and Linex Loss 1 at 10% and 5% significance levels, respectively. For CAN too, IMF predicts the economic growth rate better than OECD. Since Linex Loss 1 gives more weight to negative values and the statistic is positive, for CAN, we find that in the periods like crisis OECD made bigger forecast errors than the IMF on average. In the case of ESP and HUN, the differences in predictive ability are significant only with the absolute and quadratic losses. For ESP OECD predictions, for HUN IMF predictions outperform the other. For LUX, the EPA hypothesis can be rejected only with Linex Loss 1 at 5% level whereas for NZL we can reject it with absolute loss and Linex Loss 2 both at 5% levels.

2.5.2 Testing for Cross-sectional Dependence

As found in our Monte Carlo simulations, the increase in the number of cross-sections increases the power of EPA tests. To see if we can reject the EPA hypothesis by using cross sectional information we apply the panel tests to the dataset. However, the gain from the usage of panels depend on the degree and nature of CD. As shown in Table 2.1 for the G7 sample, the cross-country correlations between the forecast errors of both organizarions are fairly high. This is the case for the OECD sample too for which the results are not

Table 2.2: DM Test Statistics for Each Country

Country	*Absolute Loss*	*Quadratic Loss*	*Linex Loss 1*	*Linex Loss 2*	*Country*	*Absolute Loss*	*Quadratic Loss*	*Linex Loss 1*	*Linex Loss 2*
AUS	-0.6155	-0.4050	-0.2726	-0.5268	ISL	-0.5325	-0.4712	-1.4357	0.6377
	(0.5382)	(0.6855)	(0.7851)	(0.5984)		(0.5943)	(0.6375)	(0.1511)	(0.5236)
AUT	0.6885	0.1479	-0.5333	0.5927	ITA	1.0697	1.1711	1.2076	0.5369
	(0.4912)	(0.8824)	(0.5939)	(0.5534)		(0.2848)	(0.2415)	(0.2272)	(0.5913)
BEL	2.0138	1.6625	1.4534	1.3261	JPN	1.4231	1.0345	0.5934	0.5011
	(0.0440)	(0.0964)	(0.1461)	(0.1848)		(0.1547)	(0.3009)	(0.5529)	(0.6163)
CAN	1.7833	1.5011	2.2292	0.5123	KOR	0.5976	0.5560	1.2499	-0.2288
	(0.0745)	(0.1333)	(0.0258)	(0.6084)		(0.5501)	(0.5782)	(0.2113)	(0.8190)
CHE	1.0464	1.0980	1.0645	0.7237	LUX	0.9249	1.0136	1.7619	-0.5726
	(0.2954)	(0.2722)	(0.2871)	(0.4693)		(0.3550)	(0.3108)	(0.0781)	(0.5669)
CZE	-1.0617	-1.0003	-0.9317	-1.1919	MEX	-0.5196	-0.3816	0.5807	-1.1110
	(0.2884)	(0.3172)	(0.3515)	(0.2333)		(0.6034)	(0.7027)	(0.5614)	(0.2666)
DEU	-0.3686	-1.1310	-0.9157	-1.1258	NLD	0.0813	0.8709	1.2784	0.2371
	(0.7124)	(0.2581)	(0.3598)	(0.2603)		(0.9352)	(0.3838)	(0.2011)	(0.8125)
DNK	0.0445	-0.7032	-0.6089	-0.6408	NOR	0.0084	-0.6276	-0.7384	-0.6664
	(0.9645)	(0.4819)	(0.5426)	(0.5217)		(0.9933)	(0.5302)	(0.4603)	(0.5052)
ESP	-1.6955	-1.6919	-1.5269	-1.2600	NZL	-2.0726	-1.5350	-1.1797	-2.0470
	(0.0900)	(0.0907)	(0.1268)	(0.2077)		(0.0382)	(0.1248)	(0.2381)	(0.0407)
FIN	0.4240	0.1252	1.2232	-0.8274	POL	-0.4466	-0.9600	-1.0961	-0.6534
	(0.6716)	(0.9003)	(0.2213)	(0.4080)		(0.6552)	(0.3370)	(0.2730)	(0.5135)
FRA	1.4205	1.4507	1.1941	1.6433	PRT	-0.0675	0.1274	0.3290	-0.0223
	(0.1555)	(0.1469)	(0.2325)	(0.1003)		(0.9461)	(0.8987)	(0.7422)	(0.9822)
GBR	-0.2435	-1.1233	-1.4703	-0.4391	SWE	-0.6610	-0.1636	0.7728	-1.3266
	(0.8076)	(0.2613)	(0.1415)	(0.6606)		(0.5086)	(0.8701)	(0.4397)	(0.1846)
GRC	-1.0708	-1.4509	-1.2931	-1.5038	TUR	-0.0736	-0.3015	-0.1499	-0.7124
	(0.2843)	(0.1468)	(0.1960)	(0.1326)		(0.9414)	(0.7630)	(0.8809)	(0.4762)
HUN	2.3868	1.8742	1.1977	1.4255	USA	0.2005	0.0081	0.0826	-0.0416
	(0.0170)	(0.0609)	(0.2311)	(0.1540)		(0.8411)	(0.9935)	(0.9342)	(0.9668)
IRL	0.4724	0.6562	1.5501	-1.0268					
	(0.6366)	(0.5117)	(0.1211)	(0.3045)					

Note: The statistics are calculated using (8) with bandwidth 0. The values shown in parentheses are p-values.

reported to save space. Hence, before proceeding to panel tests of EPA, we analyse the CD in the two panel datasets of OECD and G7 countries. Here, we adapt the two step methodology of Bailey, Holly and Pesaran (2016). This involves testing for WCD in the first step and proceeding with spatial modeling if the null hypothesis is not rejected. If the null hypothesis is not rejected, we defactor the variables using PC methods or their cross sectional averages.

Here, we use two tests of CD. The first is the LM test of the absence of CD by Breusch and Pagan (1980) and the second one is the WCD test of Pesaran (2015). The first is a test of the joint significance of pairwise correlations between all units in the panel. The null hypothesis of this test is the absence of CD between any pair in the panel and the statistic is distributed as χ^2_q with $q = n(n-1)/2$. Hence, the test is more suitable for the cases of fixed and small n.

The null hypothesis of the second test is the absence of WCD in the process. The rejection of this null indicates the presence of SCD. Hence, an analysis of the common

Table 2.3: Weak CD Tests for the Sample of OECD Countries

	Original Data				Defactored Data			
	Absolute Loss	*Quadratic Loss*	*Linex Loss 1*	*Linex Loss 2*	*Absolute Loss*	*Quadratic Loss*	*Linex Loss 1*	*Linex Loss 2*
Breusch-Pagan LM Test	478.1028	856.2750	1,664.5419	1,350.5553	619.6212	1,063.6243	872.6455	846.1732
	(0.0078)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Pesaran's Test	0.4718	2.4395	2.8551	2.4181	0.5174	0.6088	1.3628	0.8416
	(0.6371)	(0.0147)	(0.0043)	(0.0156)	(0.6049)	(0.5427)	(0.1729)	(0.4000)

Note: Breusch-Pagan's LM Test and Pesaran's Test are calculated using (52) and (54), respectively. The values shown in parantheses are p-values.

Table 2.4: Weak CD Tests for the Sample of G7 Countries

	Original Data				Defactored Data			
	Absolute Loss	*Quadratic Loss*	*Linex Loss 1*	*Linex Loss 2*	*Absolute Loss*	*Quadratic Loss*	*Linex Loss 1*	*Linex Loss 2*
Breusch-Pagan LM Test	34.6358	51.9446	100.3906	80.2496	89.4015	173.0582	129.7162	95.2154
	(0.0309)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Pesaran's Test	3.6796	0.8368	-1.7005	4.9519	-2.4299	3.7122	-0.4214	-0.2091
	(0.0002)	(0.4027)	(0.0890)	(0.0000)	(0.0151)	(0.0002)	(0.6735)	(0.8344)

Note: Breusch-Pagan's LM Test and Pesaran's Test are calculated using (52) and (54), respectively. The values shown in parantheses are p-values.

factors in the panel is necessary. The test statistic is asymptotically normal as $n \to \infty$ and more suitable for large panels.

The results for the OECD countries are given in Table 2.3. The null hypothesis of no CD is rejected using Breusch-Pagan test for all four loss types. The number of countries is larger than the number of periods in this dataset, so the test is not very reliable. Using Pesaran's test, the null of WCD can be rejected all loss functions except the absolute loss. Therefore, it is needed to defactor the observations. We use PC methods to do so. For this, it is needed to choose the number of factors to be extracted from the panel dataset. Bai and Ng (2002) suggested several information criteria to determine the number of factors. These criteria suggest the existence of 5 common factors. After removing 5 common factors from the data, Breusch-Pagan tests on the residuals still indicate CD. Whereas, according to Pesaran's test the null hypothesis of WCD cannot be rejected. This means that the tests which allow for common factors and spatial dependence on this sample are more liable.

Table 2.4 gives the CD test results for the sample of G7 countries. In this sample too, the null hypothesis of no CD can be rejected using Breusch-Pagan test. For quadratic loss function the null of WCD cannot be rejected in traditional levels using Pesaran's test. For Linex Loss 1 and Linex Loss 2, the WCD hypothesis can be rejected at 10% level at the highest. For these loss functions, it is necessary to defactor the observations. The information criteria for this sample indicates the existence of 2 common factors. When we defactor the variables using 2 factors, the WCD hypothesis is not rejected for the two linex loss differentials. These conclusions can guide us in panel tests of EPA.

2.5.3 Panel Tests for the EPA Hypotheses

The panel EPA tests for the OECD dataset is given in Table 2.5. As before for the time series kernels we use a bandwidth of 0. For the spatial kernels we used the geographic distances between countries. The data on geographical distance come from CEPII GeoDist dataset (Mayer and Zignago, 2011). We chose the 25th percentile of the sample of distances as the bandwidth parameter in all kernel functions. The statistics for the absolute loss and Linex Loss 1 are positive, hence, OECD has a lower prediction performance in terms of bias and during the periods like crisis. However, these differences are not statistically significant. When we use quadratic loss and Linex Loss 2, the statistics are negative, therefore, overall OECD makes predictions of lower variance but once more these differences are never statistically significant.

With absolute error loss the joint EPA hypothesis can be rejected if we use Kernel robust estimates using the truncated kernel. This is not the case when common factors are used to estimate the covariance matrix. Among the other loss functions, the joint EPA is rejected only with Linex Loss 2 when common factors or truncated kernel are used. In the light of the above CD tests we find covariance estimates using common factors more reliable. Hence, the conclusion is that the differences between the predictive ability of the two organizations are significant in periods of positive errors.

Table 2.6 reports the results of overall and joint EPA tests for G7 countries. As before, there is no strong evidence against the overall EPA hypothesis using any loss type. One exception is Linex Loss 2 with non-robust or Kernel robust estimates of the variance. In this sample too, there is evidence of superior predictive ability of the OECD in positive error periods like crisis.

In the light of the Monte Carlo results, we expect more power from joint EPA tests. As in this sample n is much smaller than T, the test $J_{n,T}^{(3)}$ is preferable as it is robust to SCD and WCD. With this test the joint EPA hypothesis is rejected for all loss functions except the absolute loss. Hence, we can conclude that the predictive ability of to organizations is statistically different for G7 countries and OECD has an overall better predictive performance.

Table 2.5: Empirical Results for the Sample of OECD Countries

Overall Tests						Joint Tests					
Test	*Kernel*	*Absolute Loss*	*Quadratic Loss*	*Linex Loss 1*	*Linex Loss 2*	*Test*	*Kernel*	*Absolute Loss*	*Quadratic Loss*	*Linex Loss 1*	*Linex Loss 2*
$S^{(1)}_{n,T}$		0.1297	-0.3163	1.1938	-1.0047	$J^{(1)}_{n,T}$		32.5706	30.1859	37.9584	26.7331
		(0.8968)	(0.7518)	(0.2326)	(0.3150)			(0.2954)	(0.4048)	(0.1233)	(0.5861)
$S^{(2)}_{n,T}$	*Truncated*	0.1213	-0.2650	0.9705	-1.0101	$J^{(2)}_{n,T}$	*Truncated*	123.1218	28.8017	31.7652	7.5243
		(0.9034)	(0.7910)	(0.3318)	(0.3125)			(0.0000)	(0.4754)	(0.3303)	(1.0000)
	Bartlett	0.1258	-0.2956	1.1424	-1.0060		*Bartlett*	33.0204	27.3033	30.4338	26.8867
		(0.8999)	(0.7675)	(0.2533)	(0.3144)			(0.2769)	(0.5553)	(0.3926)	(0.5778)
	Parzen	0.1277	-0.3059	1.1796	-1.0046		*Parzen*	32.5760	27.5577	31.7036	25.6252
		(0.8984)	(0.7597)	(0.2382)	(0.3151)			(0.2952)	(0.5416)	(0.3330)	(0.6454)
	Tukey	0.1262	-0.2977	1.1622	-1.0053		*Tukey*	33.4938	27.7226	32.1140	26.3184
		(0.8995)	(0.7659)	(0.2451)	(0.3147)			(0.2583)	(0.5328)	(0.3149)	(0.6084)
	QS	0.1239	-0.2885	1.1201	-1.0061		*QS*	33.2744	28.7395	33.8395	29.3777
		(0.9014)	(0.7729)	(0.2627)	(0.3144)			(0.2668)	(0.4787)	(0.2452)	(0.4455)
$S^{(3)}_{n,T}$		0.1057	-0.2064	0.7407	-1.0312	$J^{(3)}_{n,T}$		-	-	-	-
		(0.9158)	(0.8365)	(0.4589)	(0.3024)			-	-	-	-
$S^{(4)}_{n,T}$		0.1045	-0.2046	0.7297	-1.0035	$J^{(4)}_{n,T}$		37.7560	37.3381	35.1717	49.9706
		(0.9168)	(0.8379)	(0.4656)	(0.3156)			(0.1279)	(0.1378)	(0.1990)	(0.0091)
$S^{(5)}_{n,T}$	*Bartlett*	0.1042	-0.2046	0.7298	-1.0035	$J^{(5)}_{n,T}$	*Bartlett*	33.6980	33.3348	33.9520	40.9475
		(0.9170)	(0.8379)	(0.4655)	(0.3156)			(0.2505)	(0.2644)	(0.2410)	(0.0696)

Note: Overall Tests and Joint Tests refer to the tests of the hypothesis (4) and (5) which are described in Section 3. The values shown in parantheses are p-values.

Table 2.6: Empirical Results for the Sample of G7 Countries

		Overall Tests						Joint Tests			
Test	*Kernel*	*Absolute Loss*	*Quadratic Loss*	*Linex Loss 1*	*Linex Loss 2*	*Test*	*Kernel*	*Absolute Loss*	*Quadratic Loss*	*Linex Loss 1*	*Linex Loss 2*
$S_{n,T}^{(1)}$		-0.4861	-1.1556	-0.5402	-1.7894	$J_{n,T}^{(1)}$		7.1185	8.0273	6.5588	4.2006
		(0.6269)	(0.2478)	(0.5891)	(0.0736)			(0.4166)	(0.3302)	(0.4762)	(0.7564)
$S_{n,T}^{(2)}$	*Truncated*	-0.4751	-1.1995	-0.6246	-1.6821	$J_{n,T}^{(2)}$	*Truncated*	8.8782	9.0841	6.7925	5.9435
		(0.6347)	(0.2303)	(0.5322)	(0.0925)			(0.2615)	(0.2467)	(0.4508)	(0.5464)
	Bartlett	-0.4802	-1.1534	-0.5414	-1.7830		*Bartlett*	7.1567	8.1210	6.7590	4.2936
		(0.6311)	(0.2488)	(0.5882)	(0.0746)			(0.4127)	(0.3220)	(0.4544)	(0.7454)
	Parzen	-0.4852	-1.1554	-0.5405	-1.7887		*Parzen*	7.1087	8.0301	6.5785	4.2051
		(0.6275)	(0.2479)	(0.5888)	(0.0737)			(0.4177)	(0.3299)	(0.4740)	(0.7559)
	Tukey	-0.4827	-1.1546	-0.5414	-1.7863		*Tukey*	7.1010	8.0529	6.6536	4.2306
		(0.6293)	(0.2483)	(0.5883)	(0.0741)			(0.4184)	(0.3280)	(0.4658)	(0.7529)
	QS	-0.4792	-1.1629	-0.5537	-1.7658		*QS*	7.2411	8.2040	6.5569	4.3921
		(0.6318)	(0.2449)	(0.5798)	(0.0774)			(0.4042)	(0.3150)	(0.4764)	(0.7337)
$S_{n,T}^{(3)}$		-0.3713	-1.0890	-0.6421	-1.4169	$J_{n,T}^{(3)}$		9.6218	19.2054	16.3559	18.7140
		(0.7104)	(0.2762)	(0.5208)	(0.1565)			(0.2110)	(0.0076)	(0.0221)	(0.0091)
$S_{n,T}^{(4)}$		-0.3644	-1.1699	-0.6268	-1.3859	$J_{n,T}^{(4)}$		7.5362	7.9669	7.8994	11.6253
		(0.7155)	(0.2420)	(0.5308)	(0.1658)			(0.3753)	(0.3355)	(0.3416)	(0.1136)
$S_{n,T}^{(5)}$	*Bartlett*	-0.3630	-1.1677	-0.6263	-1.3855	$J_{n,T}^{(5)}$	*Bartlett*	7.3604	8.0304	7.8994	11.5399
		(0.7166)	(0.2429)	(0.5311)	(0.1659)			(0.3923)	(0.3299)	(0.3416)	(0.1167)

Note: Overall Tests and Joint Tests refer to the tests of the hypothesis (4) and (5) which are described in Section 3. The values shown in parantheses are p-values.

2.6 Conclusion

This chapter has been concerned with the problem of testing equal predictive ability hypothesis using panel data. The test which is proposed by Diebold and Mariano (1995) has been generalized to a panel data context taking into account the complications arise from using micro and macro data sets. We derived test statistics which are robust to different forms of cross-sectional dependence, arising either from spatial dependence (weak cross-sectional dependence) and common factors (strong cross-sectional dependence) in the forecast errors.

The small sample properties of the proposed tests have been found to be satisfactory in a large set of Monte Carlo simulations. In particular, the tests which are robust to strong cross-sectional dependence are found to be correctly sized in all experiments. This is the case even in the experiments which do not involve common factors but only spatial dependence. However, their power is generally low compared to test statistics which are robust only to spatial dependence, given that forecast errors do not contain common factors. In these cases, the Monte Carlo evidence suggest to use Bartlett and Parzen kernels for correctly sized test.

Finally, the tests have been used to compare the prediction performance of the two major organizations, the OECD and IMF, on their historical economic growth forecasts. We found that IMF has an overall better performance in terms of bias whereas OECD makes predictions with less variance but the difference is not statistically significant. In a sub-sample of G7 countries OECD predictions are found to be superior to that of IMF.

A possible extension of the testing procedures proposed in this chapter is to allow to distinguish between the sources of the differences in predictive ability. As suggested in the chapter, predictive ability of different forecasters may differ through periods while on average they have equal predictive power. To deal with this situation, the conditional EPA tests of GW can be extended to our panel data framework. This is an ongoing research agenda.

Appendices

2.A Tables of Monte Carlo Results

Table 2.7: Size – DGP 1: No Factor Dependence, Low Spatial Dependence

			Overall EPA Test												Joint EPA Test										
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	3.65	4.60	4.15	3.80	4.65	12.35	12.10	11.65	12.40	13.25	$J_{n,T}^{(1)}$	10	7.55	2.40	2.60	1.55	1.95	19.35	10.90	8.35	8.15	6.85
		20	3.40	3.90	4.70	3.40	3.70	11.35	11.55	11.55	10.15	11.15		20	10.25	3.85	2.85	2.00	1.35	24.85	12.35	10.25	7.30	6.05
		30	3.25	3.40	3.80	3.45	3.20	10.20	11.05	11.40	10.90	10.25		30	13.75	4.90	3.30	2.05	1.55	32.35	14.85	11.15	8.05	6.95
		50	4.10	2.85	2.50	2.90	3.45	12.35	10.40	9.75	11.10	9.80		50	22.35	6.05	3.95	2.55	1.80	45.70	18.80	13.65	8.95	6.60
		100	3.80	3.55	4.50	4.45	3.65	11.75	10.65	12.25	12.15	11.25		100	43.60	10.50	4.80	3.15	2.00	67.15	28.50	17.10	11.20	7.95
		200	2.90	3.45	3.20	2.50	3.65	9.95	10.60	10.25	9.60	11.15		200	73.30	20.65	9.65	4.85	2.20	88.65	43.90	26.25	14.65	8.85
Truncated	$S_{n,T}^{(2)}$	10	1.65	1.45	1.20	1.20	1.35	6.35	6.60	6.05	6.15	6.45	$J_{n,T}^{(2)}$	10	25.50	13.80	8.25	4.25	2.05	35.90	24.30	18.00	11.85	8.05
		20	1.80	1.35	1.65	1.25	0.85	6.80	5.70	6.60	5.55	5.40		20	33.05	36.40	36.70	13.30	3.75	39.25	45.70	50.65	28.45	11.70
		30	1.65	0.85	0.95	0.85	1.25	5.75	5.10	6.55	4.50	5.10		30	30.50	39.60	46.30	21.35	4.75	34.20	46.85	58.25	37.95	15.85
		50	1.90	0.90	0.70	1.20	0.90	6.50	4.95	4.45	5.20	4.95		50	35.70	46.50	56.55	31.90	7.30	39.50	51.50	64.50	51.85	18.30
		100	0.95	0.95	1.20	0.80	1.10	5.90	4.85	5.80	5.40	4.85		100	39.40	54.25	71.50	63.15	13.90	41.20	57.10	75.40	79.55	33.05
		200	1.20	1.15	0.90	0.70	0.80	4.80	5.35	4.95	4.05	5.20		200	34.20	40.85	52.25	73.75	65.85	35.75	42.10	54.00	75.50	83.75
Bartlett	$S_{n,T}^{(2)}$	10	3.65	4.60	4.15	3.80	4.65	12.35	12.10	11.65	12.40	13.25	$J_{n,T}^{(2)}$	10	7.55	2.40	2.60	1.55	1.95	19.35	10.90	8.35	8.15	6.85
		20	2.20	2.20	2.90	2.05	1.90	8.45	8.45	8.70	7.40	8.00		20	15.80	5.40	3.05	1.65	1.30	33.60	14.40	11.00	7.50	5.60
		30	2.25	2.00	2.10	2.05	1.80	7.65	7.25	8.85	7.05	7.65		30	24.55	6.40	3.75	2.00	1.20	44.10	18.55	12.25	7.90	6.70
		50	2.55	1.70	1.15	2.00	2.05	8.80	7.30	6.70	8.15	7.05		50	40.70	8.40	4.55	2.55	1.55	62.05	24.10	16.30	9.65	6.30
		100	1.50	1.80	1.95	1.85	1.60	7.00	6.85	7.25	6.95	6.55		100	87.65	29.65	11.45	4.70	2.30	95.80	51.55	30.00	14.25	8.35
		200	1.45	1.65	1.25	1.10	1.40	5.75	7.05	6.20	5.90	6.90		200	99.90	70.75	34.95	11.90	3.55	100.00	87.40	58.85	30.65	12.40
Parzen	$S_{n,T}^{(2)}$	10	3.65	4.60	4.15	3.80	4.65	12.35	12.10	11.65	12.40	13.25	$J_{n,T}^{(2)}$	10	7.55	2.40	2.60	1.55	1.95	19.35	10.90	8.35	8.15	6.85
		20	3.00	2.90	3.75	2.80	3.15	10.00	9.80	9.85	8.80	9.50		20	10.50	3.65	2.35	1.45	1.25	24.25	11.70	9.40	7.15	5.45
		30	2.60	2.60	3.15	2.70	2.25	8.50	8.50	10.60	8.90	8.60		30	14.25	4.55	2.75	1.60	1.35	33.00	14.25	10.60	7.10	6.45
		50	3.40	2.35	1.70	2.50	2.70	10.85	8.75	7.90	9.75	8.65		50	22.80	5.65	3.45	2.15	1.45	46.00	17.95	12.60	8.50	5.85
		100	2.05	1.95	2.60	2.15	1.70	7.45	7.55	8.30	8.15	7.45		100	67.10	15.60	5.45	3.25	1.65	84.25	36.50	21.00	11.35	7.15
		200	1.90	1.85	1.70	1.35	1.75	6.20	7.80	6.60	6.20	7.80		200	95.65	38.15	16.10	6.30	2.10	98.80	62.60	36.75	18.40	9.30
Tukey	$S_{n,T}^{(2)}$	10	3.65	4.60	4.15	3.80	4.65	12.35	12.10	11.65	12.40	13.25	$J_{n,T}^{(2)}$	10	7.55	2.40	2.60	1.55	1.95	19.35	10.90	8.35	8.15	6.85
		20	2.20	2.20	2.85	2.20	1.90	8.40	8.50	8.65	7.50	8.05		20	14.75	5.20	2.90	1.60	1.35	32.85	14.25	10.85	7.40	5.40
		30	2.30	2.05	2.10	2.05	1.90	7.60	7.25	8.90	7.10	7.65		30	22.85	5.95	3.45	1.85	1.15	41.90	17.75	12.10	7.55	6.60
		50	2.50	1.70	1.15	2.05	2.05	8.90	7.35	6.75	8.20	7.05		50	37.50	7.85	4.30	2.50	1.50	59.35	23.25	15.60	9.40	6.35
		100	1.35	1.65	1.75	1.65	1.50	6.70	6.50	6.95	6.70	6.40		100	92.50	34.25	13.75	5.55	2.55	97.95	56.25	33.35	16.15	9.00
		200	1.25	1.55	1.15	1.00	1.15	5.40	6.55	5.90	5.45	6.65		200	100.00	76.05	38.90	13.05	3.80	100.00	90.25	62.45	32.20	13.30
QS	$S_{n,T}^{(2)}$	10	3.10	4.05	3.65	3.45	3.95	11.40	11.40	10.50	11.45	12.15	$J_{n,T}^{(2)}$	10	7.30	2.15	2.40	1.40	1.70	18.85	10.15	7.55	7.10	6.45
		20	2.00	1.75	2.50	1.70	1.30	7.85	7.45	7.60	6.65	6.85		20	30.40	7.50	4.65	2.20	1.40	50.60	20.50	13.80	9.35	6.15
		30	1.95	1.50	1.75	1.70	1.60	6.40	6.00	7.95	6.30	7.00		30	45.60	11.90	5.80	3.10	1.55	65.10	27.20	16.60	9.70	7.85
		50	2.25	1.25	1.05	1.65	1.40	7.95	6.30	5.70	6.90	6.50		50	69.15	18.25	8.30	4.00	2.05	85.20	38.05	23.45	12.20	7.30
		100	1.20	1.25	1.55	1.40	1.30	6.35	5.95	6.50	6.10	5.95		100	99.55	60.05	29.20	10.35	3.70	99.80	79.30	51.55	24.35	12.00
		200	1.25	1.45	1.10	0.95	1.00	5.15	6.05	5.45	4.75	6.05		200	100.00	98.60	77.55	32.60	7.70	100.00	99.85	90.50	56.30	21.60
	$S_{n,T}^{(3)}$	10	3.25	2.25	1.50	1.15	1.15	8.45	7.10	6.00	5.75	6.00	$J_{n,T}^{(3)}$	10		40.40	18.40	7.20	2.95		56.30	33.05	18.30	10.15
		20	3.60	2.15	1.90	1.35	0.90	9.65	7.40	6.80	5.95	5.55		20			81.95	38.95	9.55			89.20	55.60	22.95
		30	3.20	1.85	1.50	1.35	1.20	8.65	7.00	7.45	5.45	5.05		30				83.60	27.55				92.05	45.50
		50	4.10	1.55	0.90	1.40	1.10	11.05	7.40	5.50	5.75	5.65		50					83.05					91.00
		100	3.50	2.40	1.85	1.40	1.25	9.85	7.25	7.00	6.50	5.35		100										
		200	4.25	1.90	1.20	0.85	1.25	9.80	7.35	5.80	4.95	5.60		200										
Fixed	$S_{n,T}^{(4)}$	10	0.60	0.75	0.80	0.85	0.40	4.65	5.05	4.05	4.20	4.15	$J_{n,T}^{(4)}$	10	0.85	1.25	1.70	2.15	2.55	5.55	6.30	7.30	9.30	9.55
		20	0.70	1.75	1.20	1.30	0.80	5.25	6.25	6.65	5.85	6.00		20	0.55	0.65	1.00	1.70	1.50	5.60	5.45	6.40	7.30	7.00
		30	0.95	1.50	1.45	1.55	1.20	5.00	6.30	6.75	6.25	6.40		30	0.75	0.80	1.50	1.20	1.25	6.00	5.85	5.75	6.90	7.00
		50	1.65	1.50	1.15	1.90	2.35	7.90	6.75	6.45	6.80	7.15		50	2.25	1.45	0.85	1.10	1.10	8.70	4.95	5.95	5.90	5.60
		100	1.70	2.15	2.95	3.10	2.60	7.55	7.40	9.40	9.90	8.80		100	3.80	1.10	1.10	1.10	1.35	12.90	7.15	5.50	5.65	6.20
		200	2.10	2.30	2.15	2.10	3.00	7.80	8.80	8.60	8.05	10.15		200	10.25	2.15	1.75	1.15	1.15	21.75	9.30	7.20	5.55	5.25
Expanding	$S_{n,T}^{(4)}$	10	1.35	1.80	1.30	1.20	1.15	5.95	7.30	5.80	5.70	6.25	$J_{n,T}^{(4)}$	10	0.50	0.55	0.95	1.55	1.50	3.95	4.90	5.90	6.50	6.75
		20	0.70	1.75	1.20	1.30	0.80	5.25	6.25	6.65	5.85	6.00		20	0.55	0.65	1.00	1.70	1.50	5.60	5.45	6.40	7.30	7.00
		30	0.95	1.50	1.45	1.55	1.20	5.00	6.30	6.75	6.25	6.40		30	0.75	0.80	1.50	1.20	1.25	6.00	5.85	5.75	6.90	7.00
		50	1.65	1.50	1.15	1.90	2.35	7.90	6.75	6.45	6.80	7.15		50	2.25	1.45	0.85	1.10	1.10	8.70	4.95	5.95	5.90	5.60
		100	1.25	1.90	2.10	2.35	2.25	6.50	7.15	9.20	9.10	8.20		100	8.70	2.80	1.25	1.50	1.65	18.80	9.55	6.40	6.55	6.45
		200	1.90	1.95	1.80	1.70	2.85	7.25	8.00	7.90	7.65	9.65		200	16.70	4.90	1.75	1.10	1.10	27.20	13.60	8.35	5.75	5.70
Fixed	$S_{n,T}^{(5)}$	10	0.50	0.65	0.90	0.75	0.50	4.15	5.00	4.00	4.40	4.85	$J_{n,T}^{(5)}$	10	4.50	1.40	1.05	1.45	2.00	8.80	5.50	5.10	7.20	7.85
		20	0.35	1.00	0.80	1.10	0.45	3.90	5.05	5.50	5.10	5.30		20	5.95	8.90	3.70	1.15	1.25	7.90	14.60	9.85	6.60	5.75
		30	0.55	0.65	0.90	0.95	0.85	3.90	4.75	5.50	4.70	4.85		30	6.30	12.20	9.95	1.20	0.85	7.65	17.25	17.00	7.40	5.70
		50	0.75	0.60	0.50	0.95	0.75	5.65	4.35	3.80	4.95	5.30		50	7.00	13.60	15.80	1.95	0.85	8.75	18.95	24.45	7.35	5.55
		100	0.60	0.75	0.95	0.95	0.90	4.90	5.15	5.60	5.70	4.70		100	6.40	18.90	21.75	2.20	0.90	7.20	22.35	31.40	7.65	4.95
		200	0.80	0.80	0.55	0.75	0.80	4.30	5.10	4.45	3.70	5.45		200	4.25	12.05	19.40	34.65	1.35	4.75	13.60	22.30	43.15	7.10
Expanding	$S_{n,T}^{(5)}$	10	0.70	1.00	0.80	0.65	0.60	4.15	5.40	4.15	4.75	5.10	$J_{n,T}^{(5)}$	10	5.30	1.05	1.35	1.15	1.15	9.50	5.05	5.85	5.60	6.65
		20	0.35	1.00	0.80	1.10	0.45	3.90	5.05	5.50	5.10	5.30		20	5.95	8.90	3.70	1.15	1.25	7.90	14.60	9.85	6.60	5.75
		30	0.55	0.65	0.90	0.95	0.85	3.90	4.75	5.50	4.70	4.85		30	6.30	12.20	9.95	1.20	0.85	7.65	17.25	17.00	7.40	5.70
		50	0.75	0.60	0.50	0.95	0.75	5.65	4.35	3.80	4.95	5.30		50	7.00	13.60	15.80	1.95	0.85	8.75	18.95	24.45	7.35	5.55
		100	0.55	0.60	0.95	0.95	1.00	4.60	4.85	5.55	5.40	4.90		100	5.80	17.65	21.50	1.90	0.85	6.85	21.40	30.80	8.70	5.60
		200	0.65	0.95	0.55	0.75	0.80	4.70	5.35	4.35	3.85	5.45		200	3.80	11.85	18.60	33.20	1.85	4.05	13.45	21.50	41.55	7.55

Table 2.8: Size – DGP 2: Factor Dependence, Low Spatial Dependence

			Overall EPA Test												Joint EPA Test									
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	34.70	34.35	32.15	29.75	36.30	47.40	46.85	44.60	42.55	48.25	$J_{n,T}^{(1)}$	10	17.05	13.75	10.70	10.60	11.15	24.05	20.05	17.05	15.00	16.70
		20	50.20	49.35	48.90	46.90	46.55	61.60	61.95	60.10	58.35	56.80		20	22.25	17.75	15.65	13.70	13.35	28.60	22.85	20.90	17.85	17.85
		30	56.95	54.50	54.95	56.15	55.05	67.05	64.10	64.70	65.45	65.25		30	25.20	18.15	18.90	17.65	15.55	29.80	23.30	23.80	22.25	19.35
		50	64.00	64.05	63.05	65.45	64.85	71.65	72.05	71.85	74.00	73.00		50	28.50	22.50	20.20	20.55	17.05	33.85	26.55	23.50	24.10	20.50
		100	74.75	73.25	74.30	73.30	73.90	79.70	80.50	81.50	79.00	80.00		100	32.45	26.25	24.75	21.55	21.15	35.80	30.05	27.80	24.20	24.55
		200	79.80	80.95	81.30	81.25	82.00	84.70	85.15	85.60	85.60	86.55		200	36.00	29.25	25.65	26.20	24.40	38.75	31.75	27.95	28.10	26.85
Truncated	$S_{n,T}^{(2)}$	10	13.95	13.00	10.95	10.60	11.35	24.00	24.55	21.45	19.85	23.75	$J_{n,T}^{(2)}$	10	5.65	1.95	1.20	0.90	0.90	8.85	3.60	2.70	2.55	1.85
		20	11.85	10.10	9.40	7.80	8.45	22.00	21.45	19.60	18.15	18.00		20	12.00	8.20	7.90	7.20	7.55	14.70	10.60	10.05	9.15	9.45
		30	17.60	13.95	15.20	14.65	13.20	28.90	26.05	28.30	26.55	24.60		30	12.45	9.30	8.10	9.35	7.80	14.60	11.40	10.25	10.85	9.30
		50	26.35	24.70	23.00	23.90	21.25	39.50	36.30	34.65	36.45	33.85		50	12.25	8.15	7.10	7.10	6.80	14.05	9.65	8.10	8.30	7.80
		100	37.75	37.90	37.60	34.20	35.10	50.65	49.60	49.85	47.70	47.55		100	14.50	9.95	8.85	8.75	7.85	15.80	11.10	10.10	9.30	8.80
		200	42.80	40.95	40.80	40.15	41.40	53.45	52.20	52.05	52.15	53.85		200	13.45	12.35	9.30	8.35	9.30	14.60	13.20	9.90	9.10	10.00
Bartlett	$S_{n,T}^{(2)}$	10	34.70	34.35	32.15	29.75	36.30	47.40	46.85	44.60	42.55	48.25	$J_{n,T}^{(2)}$	10	17.05	13.75	10.70	10.60	11.15	24.05	20.05	17.05	15.00	16.70
		20	28.50	28.50	27.20	24.90	24.60	42.15	41.10	41.20	38.10	36.65		20	11.50	6.15	5.05	2.80	2.95	17.15	10.45	7.85	5.25	5.35
		30	36.75	34.60	35.90	35.00	32.65	49.35	46.40	47.60	47.25	46.50		30	14.10	6.05	6.05	4.35	4.20	19.65	9.60	9.30	7.15	5.85
		50	47.30	44.05	43.45	45.25	43.55	57.75	55.60	55.75	57.35	56.70		50	17.80	7.85	7.20	5.35	3.90	22.90	11.65	9.90	7.85	6.15
		100	53.70	53.15	53.70	51.05	52.10	64.00	63.10	62.60	61.65	63.65		100	23.65	8.85	5.45	4.60	3.30	28.40	11.80	8.00	6.70	5.05
		200	59.70	59.10	58.75	60.05	60.65	68.20	69.10	68.25	68.25	69.30		200	36.10	12.00	7.25	6.00	3.70	42.05	14.85	9.60	8.25	5.05
Parzen	$S_{n,T}^{(2)}$	10	34.70	34.35	32.15	29.75	36.30	47.40	46.85	44.60	42.55	48.25	$J_{n,T}^{(2)}$	10	17.05	13.75	10.70	10.60	11.15	24.05	20.05	17.05	15.00	16.70
		20	39.05	38.25	38.80	35.60	34.40	51.95	51.20	50.85	48.75	48.05		20	14.00	9.45	7.85	5.85	5.90	19.05	13.95	12.15	9.10	9.10
		30	47.40	44.50	46.05	45.55	44.20	58.20	55.25	55.95	57.45	56.15		30	16.70	9.45	9.95	8.05	6.70	21.05	13.70	13.15	12.15	10.30
		50	56.45	53.95	54.45	55.85	55.75	64.70	64.85	63.75	66.15	65.50		50	19.55	12.15	11.30	9.75	7.70	23.65	15.35	13.45	12.90	10.40
		100	60.15	60.30	59.45	57.85	59.20	69.00	68.10	68.40	67.35	68.80		100	20.55	10.90	7.95	6.65	5.90	25.20	14.00	10.45	8.60	7.85
		200	67.05	67.55	67.35	67.25	68.45	74.25	75.85	75.50	74.70	75.75		200	26.40	12.90	9.55	9.05	6.45	30.00	15.25	11.65	11.00	8.10
Tukey	$S_{n,T}^{(2)}$	10	34.70	34.35	32.15	29.75	36.30	47.40	46.85	44.60	42.55	48.25	$J_{n,T}^{(2)}$	10	17.05	13.75	10.70	10.60	11.15	24.05	20.05	17.05	15.00	16.70
		20	29.70	29.60	28.85	26.65	25.75	43.30	43.05	42.15	39.75	37.95		20	13.25	6.80	5.60	3.15	3.45	18.95	11.40	8.70	6.20	5.85
		30	38.35	36.20	37.20	36.55	34.60	50.70	47.30	48.95	48.85	47.55		30	17.10	7.35	7.05	5.25	4.80	22.75	11.40	10.70	7.85	6.75
		50	48.70	45.80	45.35	46.80	44.90	58.85	56.90	57.20	58.30	57.95		50	21.55	9.50	8.35	6.20	4.65	27.15	13.50	11.60	8.90	7.10
		100	53.75	53.30	53.85	51.15	52.30	64.10	63.15	62.65	61.65	63.80		100	47.45	15.80	10.00	7.60	5.70	56.35	21.55	13.80	10.10	8.90
		200	60.35	60.05	59.90	60.85	61.75	68.80	69.70	69.10	69.10	70.30		200	76.85	32.05	17.20	12.90	8.05	80.40	40.15	22.25	16.25	10.60
QS	$S_{n,T}^{(2)}$	10	31.10	31.80	28.35	26.50	32.15	43.75	43.25	40.15	38.45	44.95	$J_{n,T}^{(2)}$	10	14.55	11.15	8.40	7.90	7.85	19.90	16.35	13.85	12.45	13.85
		20	23.40	23.40	21.75	19.70	19.65	36.40	35.45	35.35	32.35	31.35		20	19.10	7.75	5.40	3.10	2.70	28.05	13.35	10.10	6.00	6.10
		30	31.55	28.80	31.00	29.65	27.45	44.90	41.65	43.35	42.05	40.60		30	24.70	7.90	7.35	4.50	4.05	33.65	13.90	11.75	7.75	7.05
		50	42.45	39.65	38.15	39.65	38.00	54.45	51.25	51.80	53.15	51.40		50	34.35	11.90	9.05	6.25	4.40	43.45	17.95	13.10	10.05	7.40
		100	49.65	48.45	49.20	46.55	46.50	59.75	59.70	58.75	56.95	58.60		100	77.10	23.30	13.35	8.30	5.40	85.20	32.40	19.60	11.60	9.65
		200	55.00	54.35	53.40	54.25	55.70	64.50	63.85	63.35	64.15	65.60		200	99.95	58.35	27.05	15.70	8.15	99.95	69.80	36.70	20.85	11.75
	$S_{n,T}^{(3)}$	10	4.70	2.40	1.35	1.60	1.30	10.15	8.55	6.05	6.35	5.65	$J_{n,T}^{(3)}$	10		43.25	20.40	8.95	3.85		56.35	34.50	18.90	10.60
		20	3.35	2.25	2.00	1.20	1.35	9.35	7.35	6.70	5.15	5.90		20			83.65	37.15	9.90			90.55	53.30	23.40
		30	3.90	1.95	1.85	1.50	1.10	10.30	6.50	7.75	5.80	5.40		30				83.40	26.55				90.90	45.95
		50	3.00	2.30	1.40	1.35	1.10	8.60	6.85	6.35	5.45	4.95		50					83.40					91.60
		100	3.10	1.80	1.20	1.80	0.60	8.45	7.05	5.25	5.65	4.70		100										
		200	4.10	2.05	1.50	1.45	1.60	10.00	7.30	6.00	6.50	5.00		200										
Fixed	$S_{n,T}^{(4)}$	10	0.10	0.75	0.50	0.95	1.10	5.00	5.15	4.40	4.85	4.80	$J_{n,T}^{(4)}$	10	1.50	2.80	3.65	3.35	4.20	7.65	10.25	10.75	10.20	11.80
		20	0.20	0.95	0.85	0.75	1.00	3.65	4.90	4.75	4.25	4.90		20	1.85	2.75	3.10	3.35	3.60	7.95	8.95	10.15	10.30	10.70
		30	0.20	0.50	0.85	0.65	0.85	4.20	4.45	5.50	4.60	4.85		30	2.35	2.40	2.35	2.85	2.80	8.60	8.60	8.95	9.15	9.55
		50	0.15	0.95	0.40	0.70	0.70	3.50	4.45	4.50	4.30	4.65		50	3.70	3.00	3.00	3.00	3.50	11.45	9.25	9.70	9.30	10.60
		100	0.00	0.55	0.30	1.20	0.55	3.85	4.40	3.95	4.95	4.15		100	6.45	3.20	3.65	3.30	3.30	15.95	9.55	10.15	10.75	10.55
		200	0.40	0.50	0.70	0.85	1.40	4.45	4.30	4.65	5.45	4.35		200	11.50	4.95	4.40	2.75	2.55	22.70	12.90	12.15	8.55	9.90
Expanding	$S_{n,T}^{(4)}$	10	0.10	0.55	0.50	0.95	1.05	4.85	4.95	4.10	4.60	4.65	$J_{n,T}^{(4)}$	10	1.70	2.55	3.05	3.95	3.70	7.30	9.65	10.35	9.40	10.50
		20	0.20	0.95	0.85	0.75	1.00	3.65	4.90	4.75	4.25	4.90		20	1.85	2.75	3.10	3.35	3.60	7.95	8.95	10.15	10.30	10.70
		30	0.20	0.50	0.85	0.65	0.85	4.20	4.45	5.50	4.60	4.85		30	2.35	2.40	2.35	2.85	2.80	8.60	8.60	8.95	9.15	9.55
		50	0.15	0.95	0.40	0.70	0.70	3.50	4.45	4.50	4.30	4.65		50	3.70	3.00	3.00	3.00	3.50	11.45	9.25	9.70	9.30	10.60
		100	0.00	0.55	0.30	1.20	0.55	3.90	4.40	3.95	4.95	4.15		100	11.75	3.40	4.10	3.60	3.75	23.70	11.40	11.85	10.45	11.45
		200	0.40	0.50	0.70	0.85	1.40	4.45	4.30	4.65	5.45	4.35		200	22.25	6.50	4.60	3.25	2.90	32.95	16.80	13.45	9.25	10.10
Fixed	$S_{n,T}^{(5)}$	10	0.10	0.75	0.45	0.90	1.10	4.95	5.15	4.35	4.80	4.70	$J_{n,T}^{(5)}$	10	5.80	4.00	2.55	2.75	3.00	10.20	11.15	10.15	9.55	10.90
		20	0.20	0.95	0.85	0.70	0.95	3.60	4.85	4.60	4.20	4.85		20	6.55	9.80	9.55	11.40	7.85	9.05	14.95	16.15	19.35	17.60
		30	0.20	0.50	0.80	0.55	0.80	4.10	4.40	5.30	4.45	4.70		30	5.35	11.55	12.35	11.20	5.20	7.10	15.90	19.05	20.15	13.75
		50	0.15	0.95	0.40	0.70	0.65	3.40	4.30	4.20	4.15	4.55		50	6.85	13.75	18.15	16.00	3.80	8.80	18.50	24.45	28.55	10.95
		100	0.00	0.45	0.30	1.15	0.45	3.75	4.30	3.90	4.90	4.10		100	6.25	16.00	24.50	20.25	1.45	7.10	19.35	31.10	32.45	7.55
		200	0.35	0.50	0.70	0.85	1.35	4.35	4.30	4.60	5.40	4.35		200	4.95	11.05	20.45	30.40	11.35	5.30	12.40	22.75	35.90	25.85
Expanding	$S_{n,T}^{(5)}$	10	0.05	0.40	0.50	0.85	0.95	4.55	4.85	3.85	4.50	4.55	$J_{n,T}^{(5)}$	10	6.75	4.85	4.20	3.65	3.40	11.80	10.90	11.65	10.45	10.05
		20	0.20	0.95	0.85	0.70	0.95	3.60	4.85	4.60	4.20	4.85		20	6.55	9.80	9.55	11.40	7.85	9.05	14.95	16.15	19.35	17.60
		30	0.20	0.50	0.80	0.55	0.80	4.10	4.40	5.30	4.45	4.70		30	5.35	11.55	12.35	11.20	5.20	7.10	15.90	19.05	20.15	13.75
		50	0.15	0.95	0.40	0.70	0.65	3.40	4.30	4.20	4.15	4.55		50	6.85	13.75	18.15	16.00	3.80	8.80	18.50	24.45	28.55	10.95
		100	0.00	0.50	0.30	1.15	0.45	3.80	4.35	3.90	4.90	4.10		100	5.65	16.55	22.55	17.10	1.80	6.70	20.60	28.70	30.70	8.80
		200	0.40	0.50	0.70	0.85	1.35	4.35	4.30	4.60	5.40	4.35		200	4.35	10.25	18.75	30.45	10.70	4.65	11.80	21.60	36.05	25.70

Table 2.9: Size Adjusted Power Under Homogeneous Alternative – DGP 1: No Factor Dependence, Low Spatial Dependence

Overall EPA Test

			1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S^{(1)}_{n,T}$	10	6.00	10.70	19.65	30.80	59.30	16.00	27.10	38.65	50.65	80.55
		20	10.15	22.20	32.70	61.05	92.95	25.70	45.50	55.70	82.25	97.95
		30	15.85	35.90	53.75	79.15	99.40	36.30	60.70	76.95	94.10	99.90
		50	27.85	60.05	77.75	96.60	100.00	52.25	80.80	93.55	99.20	100.00
		100	61.90	93.05	99.00	100.00	100.00	83.90	98.00	100.00	100.00	100.00
		200	92.90	99.95	100.00	100.00	100.00	97.50	100.00	100.00	100.00	100.00
Truncated	$S^{(2)}_{n,T}$	10	4.35	10.40	18.80	29.00	57.80	15.25	26.00	38.35	50.50	80.95
		20	6.80	21.85	31.55	60.05	91.45	24.60	43.05	56.30	82.10	98.00
		30	12.50	32.60	52.85	77.20	99.30	34.05	58.45	77.10	93.35	99.95
		50	25.05	58.20	78.80	96.35	100.00	50.90	81.85	93.65	99.05	100.00
		100	60.00	93.45	98.95	100.00	100.00	82.55	97.95	99.95	100.00	100.00
		200	91.30	100.00	100.00	100.00	100.00	97.45	100.00	100.00	100.00	100.00
Bartlett	$S^{(2)}_{n,T}$	10	6.00	10.70	19.65	30.80	59.30	16.00	27.10	38.65	50.65	80.55
		20	9.15	21.80	30.65	61.45	92.85	24.15	44.70	56.15	82.80	98.00
		30	15.55	35.55	54.25	79.10	99.45	35.35	61.40	77.45	94.10	99.95
		50	28.30	60.15	78.25	96.20	100.00	52.85	80.95	93.65	99.10	100.00
		100	61.00	93.20	99.15	100.00	100.00	83.50	98.00	99.95	100.00	100.00
		200	92.90	99.95	100.00	100.00	100.00	97.55	100.00	100.00	100.00	100.00
Parzen	$S^{(2)}_{n,T}$	10	6.00	10.70	19.65	30.80	59.30	16.00	27.10	38.65	50.65	80.55
		20	9.35	22.05	32.45	61.55	92.95	25.40	45.75	55.65	82.20	98.00
		30	15.40	35.45	53.70	79.55	99.40	36.00	61.35	77.25	94.20	99.90
		50	28.05	59.85	77.85	96.50	100.00	52.60	80.85	93.65	99.15	100.00
		100	60.45	93.10	99.15	100.00	100.00	83.65	97.90	99.95	100.00	100.00
		200	93.00	99.95	100.00	100.00	100.00	97.60	100.00	100.00	100.00	100.00
Tukey	$S^{(2)}_{n,T}$	10	6.00	10.70	19.65	30.80	59.30	16.00	27.10	38.65	50.65	80.55
		20	9.10	21.70	31.00	61.60	92.90	24.45	44.90	55.95	82.55	98.00
		30	14.90	35.45	54.25	79.20	99.45	35.20	61.50	77.55	94.15	99.95
		50	28.30	60.30	78.00	96.25	100.00	52.60	80.65	93.70	99.10	100.00
		100	60.85	93.20	99.20	100.00	100.00	83.50	97.95	99.95	100.00	100.00
		200	92.85	99.95	100.00	100.00	100.00	97.70	100.00	100.00	100.00	100.00
QS	$S^{(2)}_{n,T}$	10	5.80	10.75	19.85	30.95	59.25	15.85	27.45	38.85	50.25	80.95
		20	8.70	21.10	30.70	60.90	92.20	24.05	44.60	56.40	82.60	98.00
		30	14.60	34.65	54.20	78.75	99.40	34.75	60.60	77.50	93.75	99.95
		50	28.15	60.10	79.80	96.20	100.00	52.25	80.95	93.60	99.10	100.00
		100	60.90	93.15	99.15	100.00	100.00	82.85	97.95	99.95	100.00	100.00
		200	92.50	99.95	100.00	100.00	100.00	97.65	100.00	100.00	100.00	100.00
	$S^{(3)}_{n,T}$	10	4.95	9.15	15.15	30.65	57.70	12.50	25.05	36.10	49.15	79.15
		20	5.35	18.80	30.45	61.40	92.65	20.75	41.95	52.05	81.35	98.00
		30	9.30	26.85	53.60	76.05	99.25	27.95	54.80	77.15	92.85	99.95
		50	18.75	49.00	75.20	95.65	100.00	45.50	76.00	92.75	98.95	100.00
		100	43.70	84.30	98.40	100.00	100.00	73.15	96.40	99.85	100.00	100.00
		200	76.65	99.90	100.00	100.00	100.00	93.95	100.00	100.00	100.00	100.00
Fixed	$S^{(4)}_{n,T}$	10	3.25	5.85	15.25	25.15	57.80	11.95	23.50	34.45	45.20	80.05
		20	5.30	19.70	29.65	56.55	90.95	19.95	41.00	55.65	81.45	98.05
		30	8.65	24.85	53.80	75.20	99.10	29.45	58.40	76.60	93.15	99.90
		50	19.75	51.50	74.80	96.30	100.00	47.05	77.90	93.40	99.10	100.00
		100	46.00	87.05	98.95	100.00	100.00	78.30	97.15	99.90	100.00	100.00
		200	82.60	100.00	100.00	100.00	100.00	95.55	100.00	100.00	100.00	100.00
Expanding	$S^{(4)}_{n,T}$	10	4.20	6.30	17.75	27.30	56.95	13.20	24.60	36.20	47.70	79.10
		20	5.30	19.70	29.65	56.55	90.95	19.95	41.00	55.65	81.45	98.05
		30	8.65	24.85	53.80	75.20	99.10	29.45	58.40	76.60	93.15	99.90
		50	19.75	51.50	74.80	96.30	100.00	47.05	77.90	93.40	99.10	100.00
		100	41.95	85.20	98.75	100.00	100.00	76.40	97.10	99.90	100.00	100.00
		200	78.45	99.95	100.00	100.00	100.00	95.25	100.00	100.00	100.00	100.00
Fixed	$S^{(5)}_{n,T}$	10	3.40	6.45	15.05	24.80	57.40	12.65	23.70	34.25	46.70	79.25
		20	5.05	19.50	30.60	58.20	91.65	19.45	40.90	53.35	81.70	98.05
		30	9.80	27.75	52.30	74.70	99.35	30.20	57.30	76.05	92.95	99.90
		50	18.15	51.35	74.65	96.15	100.00	46.95	78.20	92.90	98.95	100.00
		100	43.85	87.15	98.70	100.00	100.00	77.15	97.10	99.90	100.00	100.00
		200	81.20	100.00	100.00	100.00	100.00	95.10	100.00	100.00	100.00	100.00
Expanding	$S^{(5)}_{n,T}$	10	7.00	9.85	23.80	30.05	62.50	16.35	28.80	40.25	52.15	83.00
		20	7.90	25.40	37.10	64.10	93.55	24.30	45.15	58.30	84.55	98.55
		30	14.15	35.10	59.80	80.75	99.55	35.45	61.85	79.80	94.20	99.90
		50	24.25	58.60	79.35	97.15	100.00	51.20	81.80	94.85	99.15	100.00
		100	46.65	88.95	98.90	100.00	100.00	78.45	97.65	100.00	100.00	100.00
		200	83.40	100.00	100.00	100.00	100.00	96.25	100.00	100.00	100.00	100.00

Joint EPA Test

			1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$J^{(1)}_{n,T}$	10	0.80	2.00	3.10	6.55	22.50	6.55	9.80	12.55	18.90	46.25
		20	1.45	2.65	5.85	16.25	38.80	6.30	11.75	15.65	31.55	63.35
		30	2.00	4.45	5.80	17.90	59.60	7.65	13.70	19.80	39.65	83.05
		50	1.55	4.35	11.55	25.95	81.15	9.25	15.65	27.05	48.60	93.20
		100	2.35	5.15	19.10	53.40	96.65	10.35	22.55	41.80	77.40	99.45
		200	3.50	17.20	36.00	80.90	99.95	13.65	39.25	61.20	94.20	100.00
Truncated	$J^{(2)}_{n,T}$	10	0.50	1.50	3.10	4.85	21.15	2.95	7.60	10.10	18.30	46.35
		20	0.85	0.45	1.00	8.35	33.35	3.25	3.15	5.55	25.50	58.65
		30	0.85	0.55	0.80	7.40	51.85	2.80	2.65	5.40	27.80	78.00
		50	0.60	0.20	0.60	12.90	74.25	3.05	3.20	3.30	36.90	90.50
		100	0.25	0.35	0.35	31.05	95.25	2.40	2.75	4.20	56.05	98.85
		200	0.65	0.50	0.65	0.35	99.80	2.45	2.20	2.70	5.65	99.90
Bartlett	$J^{(2)}_{n,T}$	10	0.80	2.00	3.10	6.55	22.50	6.55	9.80	12.55	18.90	46.25
		20	1.20	2.30	4.85	13.95	38.05	6.75	10.85	15.30	32.65	63.00
		30	1.85	4.15	6.05	17.00	58.95	7.35	12.90	19.25	38.20	82.45
		50	1.40	4.50	11.90	24.40	81.90	7.65	14.00	24.15	47.05	93.30
		100	1.95	6.55	16.65	45.00	96.15	10.30	21.35	38.30	74.60	99.45
		200	3.35	14.65	36.00	80.15	99.95	11.95	32.00	58.30	92.60	100.00
Parzen	$J^{(2)}_{n,T}$	10	0.80	2.00	3.10	6.55	22.50	6.55	9.80	12.55	18.90	46.25
		20	1.50	2.70	5.05	15.10	38.80	6.50	11.80	15.95	32.55	63.70
		30	1.50	4.00	5.75	18.25	60.45	7.65	13.60	19.75	39.15	83.00
		50	1.50	4.35	11.75	25.45	81.45	8.80	14.75	26.10	47.50	92.95
		100	1.90	6.65	18.50	47.55	96.55	10.45	21.70	39.20	75.55	99.45
		200	3.00	16.35	40.05	80.40	100.00	11.75	33.55	60.00	93.65	100.00
Tukey	$J^{(2)}_{n,T}$	10	0.80	2.00	3.10	6.55	22.50	6.55	9.80	12.55	18.90	46.25
		20	1.30	2.35	4.70	14.15	38.20	6.70	10.90	15.55	32.90	63.75
		30	1.85	4.15	5.95	17.05	59.00	7.45	13.35	19.65	38.50	82.30
		50	1.35	4.75	11.40	24.75	81.50	7.60	14.80	24.70	46.45	93.10
		100	2.20	6.60	16.00	43.80	96.15	8.75	19.95	38.20	73.85	99.45
		200	2.90	14.30	35.95	80.20	99.95	11.75	31.25	57.05	92.50	100.00
QS	$J^{(2)}_{n,T}$	10	0.85	2.15	3.10	6.60	22.70	6.90	9.35	12.50	19.45	46.75
		20	1.15	2.15	4.80	13.95	37.25	6.45	10.00	14.80	31.65	62.95
		30	1.90	3.75	5.40	16.10	58.40	6.75	13.25	18.05	36.60	81.65
		50	1.95	5.05	9.95	23.10	80.90	6.15	13.55	24.20	47.25	92.95
		100	2.15	6.20	15.70	43.10	95.70	8.65	18.85	35.45	73.70	99.30
		200	2.45	9.60	31.00	78.10	99.95	9.50	28.35	53.75	90.85	100.00
	$J^{(3)}_{n,T}$	10		1.55	2.55	4.85	20.15		7.60	8.70	15.15	42.85
		20			1.80	7.70	26.55			9.75	21.45	55.90
		30				4.55	38.20				18.55	64.65
		50					38.55					70.95
		100										
		200										
Fixed	$J^{(4)}_{n,T}$	10	0.75	1.40	2.55	3.95	16.00	4.80	7.25	8.10	13.30	37.35
		20	1.20	2.25	3.40	8.40	26.40	5.70	7.50	11.55	22.35	53.65
		30	0.90	2.20	4.00	6.05	44.45	4.80	8.30	13.70	25.75	68.55
		50	1.25	2.45	4.75	18.05	55.00	5.50	8.00	15.35	29.55	77.35
		100	1.00	3.00	5.20	19.55	68.30	4.45	8.80	15.85	40.15	83.00
		200	0.75	3.20	6.30	20.75	39.60	4.35	8.90	18.30	33.75	52.50
Expanding	$J^{(4)}_{n,T}$	10	1.35	1.75	2.35	4.25	18.60	5.70	7.90	10.45	16.10	39.35
		20	1.20	2.25	3.40	8.40	26.40	5.70	7.50	11.55	22.35	53.65
		30	0.90	2.20	4.00	6.05	44.45	4.80	8.30	13.70	25.75	68.55
		50	1.25	2.45	4.75	18.05	55.00	5.50	8.00	15.35	29.55	77.35
		100	0.65	1.85	4.15	12.60	53.40	2.60	5.65	9.90	28.30	72.40
		200	0.55	1.45	3.15	11.60	25.70	3.70	5.40	9.85	19.70	37.60
Fixed	$J^{(5)}_{n,T}$	10	0.45	1.35	2.25	4.65	15.55	3.30	6.85	10.00	13.30	37.45
		20	0.65	0.45	1.05	6.10	22.60	3.35	3.25	7.05	20.80	51.00
		30	0.30	0.25	0.25	5.55	37.15	3.00	2.50	4.85	21.50	64.25
		50	0.55	0.45	0.50	8.10	48.45	2.80	2.70	3.60	22.85	77.20
		100	0.50	0.30	0.15	8.40	61.20	2.40	3.15	2.60	24.85	79.20
		200	0.80	0.65	0.60	0.30	29.80	3.10	2.85	2.90	3.05	40.65
Expanding	$J^{(5)}_{n,T}$	10	0.85	5.35	10.25	11.60	29.65	6.00	16.80	22.10	27.75	53.90
		20	0.20	0.85	2.20	24.60	46.85	3.65	5.60	25.35	46.10	72.80
		30	0.80	0.55	1.00	29.40	70.75	4.70	4.00	16.75	55.65	87.10
		50	0.65	0.70	0.65	43.00	85.20	4.15	3.25	7.15	66.95	95.50
		100	1.00	0.45	1.00	51.25	89.45	4.25	3.40	5.95	70.20	96.20
		200	0.45	0.60	0.45	1.05	70.95	5.45	3.50	5.05	6.15	79.95

Table 2.10: Size Adjusted Power Under Homogeneous Alternative – DGP 2: Factor Dependence, Low Spatial Dependence

			Overall EPA Test												Joint EPA Test										
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S^{(1)}_{n,T}$	10	39.85	78.30	95.55	99.75	100.00	65.55	90.70	99.00	99.95	100.00	$J^{(1)}_{n,T}$	10	39.95	85.30	97.60	99.90	100.00	69.20	94.55	99.65	100.00	100.00
		20	48.05	77.35	94.75	99.75	100.00	69.35	93.35	99.15	100.00	100.00		20	50.35	83.25	97.95	100.00	100.00	73.15	96.90	99.80	100.00	100.00
		30	45.15	85.65	96.20	99.80	100.00	71.70	95.60	99.15	100.00	100.00		30	40.65	90.00	98.70	100.00	100.00	75.85	98.05	99.90	100.00	100.00
		50	51.50	82.25	98.15	99.80	100.00	74.45	95.60	99.40	100.00	100.00		50	53.30	87.80	99.40	99.95	100.00	79.75	98.60	99.95	100.00	100.00
		100	51.20	88.35	98.35	99.90	100.00	76.30	96.10	99.65	100.00	100.00		100	56.25	94.40	99.80	100.00	100.00	81.35	98.85	99.95	100.00	100.00
		200	47.25	86.50	97.45	99.95	100.00	70.25	96.50	99.75	100.00	100.00		200	49.00	93.80	99.50	100.00	100.00	75.90	98.55	100.00	100.00	100.00
Truncated	$S^{(2)}_{n,T}$	10	33.10	75.80	94.65	99.55	100.00	63.45	90.25	98.85	99.95	100.00	$J^{(2)}_{n,T}$	10	29.25	75.50	95.90	99.65	99.95	60.05	93.00	98.85	99.95	99.95
		20	39.80	70.55	93.60	99.55	100.00	63.65	91.90	99.00	100.00	100.00		20	1.45	1.65	2.50	3.95	19.65	12.70	29.05	52.20	71.55	84.90
		30	29.90	82.95	95.85	99.80	100.00	65.65	94.95	99.00	100.00	100.00		30	2.20	1.75	2.95	6.90	11.35	13.15	18.75	34.30	54.35	77.60
		50	38.65	75.20	97.55	99.80	100.00	70.25	94.35	99.35	99.95	100.00		50	2.10	2.30	4.95	6.05	44.55	13.55	28.05	48.70	73.10	84.20
		100	46.25	84.80	97.70	99.90	100.00	71.75	96.05	99.65	100.00	100.00		100	2.30	3.00	2.65	3.60	10.75	12.75	26.00	44.30	67.25	83.00
		200	34.80	83.85	96.15	99.95	100.00	65.70	95.40	99.60	100.00	100.00		200	2.10	2.40	3.00	7.75	10.75	11.30	17.10	33.25	53.60	70.45
Bartlett	$S^{(2)}_{n,T}$	10	39.85	78.30	95.55	99.75	100.00	65.55	90.70	99.00	99.95	100.00	$J^{(2)}_{n,T}$	10	39.95	85.30	97.60	99.90	100.00	69.20	94.55	99.65	100.00	100.00
		20	42.95	74.55	93.80	99.70	100.00	65.90	92.60	99.05	100.00	100.00		20	48.30	85.90	99.15	100.00	100.00	74.50	98.35	100.00	100.00	100.00
		30	36.05	84.15	96.25	99.80	100.00	67.75	94.90	99.05	100.00	100.00		30	36.70	95.15	99.70	100.00	100.00	77.25	99.25	99.95	100.00	100.00
		50	45.65	78.60	97.95	99.80	100.00	72.05	94.90	99.35	99.95	100.00		50	53.45	92.55	99.95	100.00	100.00	83.15	99.85	100.00	100.00	100.00
		100	47.15	84.80	97.80	99.90	100.00	73.00	96.00	99.65	100.00	100.00		100	62.70	99.50	99.95	100.00	100.00	91.70	100.00	100.00	100.00	100.00
		200	38.15	84.60	96.55	99.95	100.00	66.70	95.65	99.65	100.00	100.00		200	41.10	100.00	100.00	100.00	100.00	89.60	100.00	100.00	100.00	100.00
Parzen	$S^{(2)}_{n,T}$	10	39.85	78.30	95.55	99.75	100.00	65.55	90.70	99.00	99.95	100.00	$J^{(2)}_{n,T}$	10	39.95	85.30	97.60	99.90	100.00	69.20	94.55	99.65	100.00	100.00
		20	45.00	76.45	94.10	99.70	100.00	67.60	92.85	99.10	100.00	100.00		20	47.00	83.15	98.55	100.00	100.00	73.15	97.25	99.85	100.00	100.00
		30	41.35	84.30	96.45	99.80	100.00	69.15	95.15	99.20	100.00	100.00		30	38.50	91.75	99.20	100.00	100.00	75.45	98.45	99.95	100.00	100.00
		50	48.10	80.10	98.00	99.80	100.00	73.05	95.25	99.35	100.00	100.00		50	51.40	87.55	99.75	100.00	100.00	80.30	99.20	100.00	100.00	100.00
		100	47.95	85.80	97.90	99.90	100.00	74.20	95.95	99.65	100.00	100.00		100	58.75	98.85	99.95	100.00	100.00	88.20	99.85	100.00	100.00	100.00
		200	40.95	85.05	97.00	99.95	100.00	67.20	95.70	99.70	100.00	100.00		200	48.80	99.40	100.00	100.00	100.00	85.40	100.00	100.00	100.00	100.00
Tukey	$S^{(2)}_{n,T}$	10	39.85	78.30	95.55	99.75	100.00	65.55	90.70	99.00	99.95	100.00	$J^{(2)}_{n,T}$	10	39.95	85.30	97.60	99.90	100.00	69.20	94.55	99.65	100.00	100.00
		20	43.35	74.85	93.75	99.70	100.00	66.20	92.60	99.05	100.00	100.00		20	45.75	87.30	99.25	100.00	100.00	74.30	98.30	100.00	100.00	100.00
		30	36.60	84.25	96.35	99.80	100.00	67.90	94.95	99.10	100.00	100.00		30	32.20	95.10	99.65	100.00	100.00	75.75	99.25	99.95	100.00	100.00
		50	46.40	78.65	97.95	99.80	100.00	72.05	95.00	99.35	100.00	100.00		50	44.70	92.30	99.85	100.00	100.00	80.40	99.60	99.95	100.00	100.00
		100	47.30	84.75	97.80	99.90	100.00	73.05	95.95	99.65	100.00	100.00		100	28.10	99.75	100.00	100.00	100.00	88.60	99.90	100.00	100.00	100.00
		200	39.05	84.70	96.75	99.95	100.00	66.90	95.60	99.65	100.00	100.00		200	3.60	99.45	100.00	100.00	100.00	63.20	99.55	100.00	100.00	100.00
QS	$S^{(2)}_{n,T}$	10	38.65	78.15	95.20	99.70	100.00	64.50	90.35	99.00	99.95	100.00	$J^{(2)}_{n,T}$	10	38.45	84.75	97.70	99.90	100.00	69.10	94.70	99.75	100.00	100.00
		20	42.30	73.20	93.90	99.70	100.00	65.80	92.35	99.00	100.00	100.00		20	51.20	89.70	99.75	100.00	100.00	77.70	99.15	100.00	100.00	100.00
		30	34.35	84.40	96.25	99.80	100.00	67.50	94.95	99.05	100.00	100.00		30	37.60	97.50	99.90	100.00	100.00	79.55	99.70	100.00	100.00	100.00
		50	43.95	77.00	97.95	99.80	100.00	71.65	94.55	99.35	99.95	100.00		50	59.80	97.50	100.00	100.00	100.00	88.30	100.00	100.00	100.00	100.00
		100	46.35	84.65	97.80	99.90	100.00	72.65	96.00	99.65	100.00	100.00		100	72.95	99.90	100.00	100.00	100.00	96.15	100.00	100.00	100.00	100.00
		200	37.10	84.45	96.50	99.95	100.00	66.35	95.65	99.65	100.00	100.00		200	60.15	100.00	100.00	100.00	100.00	96.60	100.00	100.00	100.00	100.00
	$S^{(3)}_{n,T}$	10	28.90	70.90	93.85	99.45	100.00	56.55	89.35	98.65	99.95	100.00	$J^{(3)}_{n,T}$	10		41.20	90.75	99.80	100.00		77.30	98.00	100.00	100.00
		20	35.00	69.65	92.55	99.60	100.00	62.10	91.50	98.95	100.00	100.00		20			75.10	100.00	100.00			94.15	100.00	100.00
		30	21.70	79.25	95.10	99.80	100.00	63.70	94.50	98.80	100.00	100.00		30				100.00	100.00				100.00	100.00
		50	33.60	73.75	97.50	99.75	100.00	67.95	93.90	99.30	99.95	100.00		50					100.00					100.00
		100	41.95	83.20	96.95	99.85	100.00	68.95	95.55	99.65	100.00	100.00		100										
		200	29.00	83.05	95.75	99.95	100.00	63.60	95.25	99.50	100.00	100.00		200										
Fixed	$S^{(4)}_{n,T}$	10	29.40	71.75	94.05	99.55	100.00	57.25	89.50	98.65	99.95	100.00	$J^{(4)}_{n,T}$	10	0.90	8.00	36.05	95.80	100.00	4.80	33.65	84.15	99.75	100.00
		20	35.35	69.80	92.65	99.60	100.00	61.95	91.55	98.95	100.00	100.00		20	1.75	12.60	41.75	95.65	100.00	4.95	28.90	68.80	100.00	100.00
		30	22.25	79.55	95.10	99.80	100.00	63.95	94.50	98.80	100.00	100.00		30	1.45	15.65	42.80	96.30	100.00	5.80	29.15	68.60	99.85	100.00
		50	33.65	73.90	97.60	99.75	100.00	68.25	93.95	99.30	99.95	100.00		50	2.85	19.95	49.70	96.90	100.00	6.45	31.10	69.25	98.75	100.00
		100	41.90	83.30	97.00	99.85	100.00	69.35	95.60	99.65	100.00	100.00		100	3.50	26.25	61.25	96.15	100.00	6.85	36.05	72.10	98.35	100.00
		200	29.20	83.05	95.85	99.95	100.00	63.60	95.30	99.50	100.00	100.00		200	6.20	32.25	69.35	97.55	100.00	9.10	39.80	77.10	99.15	100.00
Expanding	$S^{(4)}_{n,T}$	10	29.55	71.85	94.20	99.55	100.00	57.10	89.70	98.65	99.95	100.00	$J^{(4)}_{n,T}$	10	2.80	14.10	38.50	90.60	99.95	10.65	39.95	83.10	99.50	100.00
		20	35.35	69.80	92.65	99.60	100.00	61.95	91.55	98.95	100.00	100.00		20	1.75	12.60	41.75	95.65	100.00	4.95	28.90	68.80	100.00	100.00
		30	22.25	79.55	95.10	99.80	100.00	63.95	94.50	98.80	100.00	100.00		30	1.45	15.65	42.80	96.30	100.00	5.80	29.15	68.60	99.85	100.00
		50	33.65	73.90	97.60	99.75	100.00	68.25	93.95	99.30	99.95	100.00		50	2.85	19.95	49.70	96.90	100.00	6.45	31.10	69.25	98.75	100.00
		100	41.90	83.30	96.95	99.85	100.00	69.35	95.60	99.65	100.00	100.00		100	0.00	0.00	0.00	0.05	0.00	0.00	0.05	0.05	0.05	0.35
		200	29.15	83.05	95.75	99.95	100.00	63.60	95.25	99.50	100.00	100.00		200	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fixed	$S^{(5)}_{n,T}$	10	29.45	72.00	94.25	99.55	100.00	57.40	89.70	98.65	99.95	100.00	$J^{(5)}_{n,T}$	10	0.40	1.25	34.60	96.80	100.00	2.20	18.40	84.10	99.80	100.00
		20	35.20	70.25	92.60	99.60	100.00	62.20	91.55	98.90	100.00	100.00		20	0.15	0.15	0.35	1.55	93.25	1.75	1.75	3.45	28.60	98.55
		30	22.50	80.15	95.10	99.80	100.00	64.00	94.55	98.80	100.00	100.00		30	0.45	0.35	0.40	0.90	99.40	2.25	2.00	3.30	38.45	99.70
		50	33.60	74.00	97.65	99.75	100.00	68.45	93.95	99.30	99.95	100.00		50	0.20	0.25	0.30	0.90	99.65	1.55	1.75	1.65	27.35	99.75
		100	41.95	83.35	97.05	99.85	100.00	69.40	95.60	99.65	100.00	100.00		100	0.30	0.20	0.20	0.50	99.65	1.20	1.30	2.00	30.55	99.70
		200	29.85	83.05	95.85	99.95	100.00	63.70	95.30	99.55	100.00	100.00		200	0.05	0.35	0.30	0.50	96.05	1.10	1.20	1.50	2.80	96.55
Expanding	$S^{(5)}_{n,T}$	10	31.00	72.50	94.20	99.55	100.00	58.45	89.70	98.65	99.95	100.00	$J^{(5)}_{n,T}$	10	1.15	2.00	2.90	90.30	99.65	12.75	46.00	84.80	98.75	99.70
		20	35.35	70.40	92.70	99.60	100.00	62.45	91.55	98.90	100.00	100.00		20	0.95	1.45	2.25	9.60	96.90	8.15	11.85	26.05	75.50	97.85
		30	22.60	80.15	95.10	99.80	100.00	64.35	94.55	98.85	100.00	100.00		30	2.30	2.45	2.35	9.45	99.45	9.25	13.80	27.10	85.50	99.45
		50	33.70	74.10	97.65	99.75	100.00	68.70	93.95	99.30	99.95	100.00		50	1.60	1.30	2.15	14.70	100.00	7.60	11.80	17.95	86.85	100.00
		100	42.00	83.30	97.05	99.85	100.00	69.35	95.60	99.65	100.00	100.00		100	0.90	0.55	0.20	0.25	1.35	3.65	2.30	1.00	1.15	3.70
		200	29.75	83.05	95.85	99.95	100.00	63.65	95.30	99.50	100.00	100.00		200	0.30	0.30	0.15	0.00	0.00	1.65	0.80	0.50	0.05	0.00

Table 2.11: Size Adjusted Power Under Heterogeneous Alternative – DGP 1: No Factor Dependence, Low Spatial Dependence

			Overall EPA Test												Joint EPA Test										
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	1.25	1.25	1.35	1.60	1.80	5.00	5.30	5.35	6.55	7.20	$J_{n,T}^{(1)}$	10	0.80	1.40	1.65	3.05	5.45	5.80	7.15	8.55	10.00	16.40
		20	1.30	1.30	1.40	1.60	2.25	5.30	5.90	6.05	6.45	7.70		20	1.45	1.85	2.10	3.35	8.55	6.25	7.30	8.50	14.15	27.15
		30	1.00	1.25	1.65	1.75	1.95	4.95	5.65	5.95	7.20	8.90		30	1.30	2.00	2.95	5.05	13.75	6.15	7.95	9.20	14.45	32.65
		50	1.05	1.45	1.55	1.55	2.55	4.95	5.45	6.25	6.60	8.40		50	1.40	1.75	3.35	5.40	21.15	6.50	9.30	12.85	20.05	48.10
		100	1.20	1.40	1.75	2.20	1.95	5.55	5.90	5.60	6.75	9.00		100	1.65	3.20	5.85	13.00	45.05	6.55	10.55	17.45	27.80	68.45
		200	1.30	1.05	1.45	1.65	3.50	5.90	6.50	6.35	7.50	9.45		200	1.95	4.05	7.85	23.80	75.90	7.30	14.30	22.20	44.45	90.95
Truncated	$S_{n,T}^{(2)}$	10	1.00	1.15	1.25	1.55	1.70	5.60	5.15	5.25	6.05	7.15	$J_{n,T}^{(2)}$	10	1.05	0.40	0.85	1.05	6.75	3.45	4.60	7.15	11.10	19.50
		20	1.05	1.35	1.15	1.70	2.55	5.40	5.45	5.55	6.40	7.90		20	0.85	0.60	0.65	2.55	10.25	2.25	3.30	4.25	11.55	25.35
		30	1.10	1.25	1.45	1.60	1.95	5.00	5.70	5.65	7.15	8.85		30	0.40	0.50	0.35	1.40	14.25	2.65	2.65	4.85	12.65	32.90
		50	0.95	1.25	1.70	1.25	2.50	5.15	5.35	6.25	6.60	8.95		50	0.45	0.40	0.70	1.75	18.85	2.80	3.40	3.25	13.25	44.95
		100	1.10	1.35	1.35	2.20	2.00	5.90	5.85	5.85	7.10	9.20		100	0.55	0.25	0.95	4.50	44.40	3.15	3.10	4.50	20.50	68.35
		200	1.20	1.05	1.50	1.65	4.05	5.35	6.20	6.35	7.70	9.95		200	0.25	0.85	0.70	0.25	62.70	1.50	3.40	3.20	3.50	84.25
Bartlett	$S_{n,T}^{(2)}$	10	1.25	1.25	1.35	1.60	1.80	5.00	5.30	5.35	6.55	7.20	$J_{n,T}^{(2)}$	10	0.80	1.40	1.65	3.05	5.45	5.80	7.15	8.55	10.00	16.40
		20	1.00	1.05	1.40	1.70	2.45	5.40	5.80	5.90	6.15	8.05		20	1.05	2.00	3.15	3.65	9.60	6.40	6.50	9.15	14.65	28.25
		30	1.00	1.15	1.45	1.60	1.85	5.30	5.80	6.30	6.95	8.70		30	1.20	1.80	2.80	5.45	15.90	5.90	8.20	9.90	14.75	34.35
		50	1.00	1.55	1.60	1.40	2.50	5.20	5.65	6.20	6.80	8.70		50	1.40	2.10	2.65	6.55	21.80	6.60	8.75	13.65	19.75	49.65
		100	1.10	1.35	1.60	2.25	1.85	5.50	6.00	5.75	6.85	9.15		100	1.45	3.80	4.90	13.20	45.50	7.15	11.35	18.15	29.50	70.80
		200	1.25	1.10	1.50	2.00	3.75	5.55	6.30	6.25	7.50	9.50		200	1.25	3.55	6.60	23.30	76.80	7.60	13.45	21.90	44.95	91.95
Parzen	$S_{n,T}^{(2)}$	10	1.25	1.25	1.35	1.60	1.80	5.00	5.30	5.35	6.55	7.20	$J_{n,T}^{(2)}$	10	0.80	1.40	1.65	3.05	5.45	5.80	7.15	8.55	10.00	16.40
		20	1.20	1.20	1.50	1.70	2.50	5.30	5.95	5.95	6.20	7.90		20	1.00	2.00	2.75	4.05	8.85	6.10	7.20	9.05	15.20	27.40
		30	0.95	1.20	1.45	1.75	1.85	5.10	5.90	6.10	7.30	8.95		30	1.45	2.15	2.45	4.95	14.80	6.20	7.80	9.45	14.55	33.15
		50	0.95	1.35	1.60	1.50	2.60	5.00	5.45	6.30	6.90	8.60		50	1.60	1.85	3.05	6.50	21.85	6.45	8.85	12.35	20.10	49.30
		100	1.20	1.30	1.60	2.30	1.90	5.70	5.85	5.70	6.65	9.10		100	1.30	3.70	4.95	13.65	45.35	6.95	10.55	20.15	29.35	70.55
		200	1.25	1.15	1.45	2.00	3.75	5.75	6.25	6.40	7.50	9.55		200	1.35	3.55	7.60	23.15	77.35	7.15	14.25	22.75	46.25	92.30
Tukey	$S_{n,T}^{(2)}$	10	1.25	1.25	1.35	1.60	1.80	5.00	5.30	5.35	6.55	7.20	$J_{n,T}^{(2)}$	10	0.80	1.40	1.65	3.05	5.45	5.80	7.15	8.55	10.00	16.40
		20	1.00	1.05	1.45	1.70	2.45	5.40	5.85	5.90	6.05	8.05		20	1.05	2.00	2.95	3.45	9.40	6.35	6.75	9.90	14.90	28.70
		30	0.95	1.20	1.35	1.60	1.85	5.25	5.90	6.40	6.90	8.75		30	1.40	1.85	2.70	5.60	15.60	5.60	8.15	9.80	15.10	34.25
		50	0.95	1.45	1.60	1.40	2.50	5.20	5.65	6.20	6.80	8.70		50	1.40	2.10	2.85	6.70	21.55	6.70	8.40	13.30	19.90	49.65
		100	1.05	1.35	1.65	2.20	1.85	5.45	6.05	5.70	6.85	9.10		100	1.45	3.35	4.55	13.05	45.20	6.75	11.00	18.95	30.25	70.35
		200	1.20	1.10	1.50	2.00	3.75	5.60	6.25	6.25	7.50	9.55		200	1.10	3.60	7.00	22.75	77.35	7.50	13.55	23.00	45.05	92.35
QS	$S_{n,T}^{(2)}$	10	1.20	1.20	1.20	1.65	1.80	5.20	5.10	5.45	6.60	7.15	$J_{n,T}^{(2)}$	10	0.85	1.45	1.65	3.30	5.50	5.55	6.85	8.20	10.35	16.40
		20	1.05	1.20	1.25	1.50	2.40	5.30	5.75	5.70	6.25	8.05		20	1.20	2.20	2.50	3.70	10.55	5.70	6.60	8.90	14.85	27.80
		30	1.10	1.15	1.45	1.65	1.80	5.15	5.80	6.30	7.05	8.70		30	1.30	1.60	2.75	5.25	16.65	5.30	8.30	10.05	15.70	34.50
		50	1.05	1.50	1.60	1.25	2.50	5.20	5.55	6.30	6.65	8.55		50	1.20	1.90	2.60	5.95	21.00	6.15	8.50	13.15	19.95	49.05
		100	1.15	1.35	1.50	2.20	1.95	5.60	6.00	5.80	6.90	9.20		100	1.40	4.20	4.35	12.25	46.95	6.65	10.65	16.90	30.60	69.90
		200	1.20	1.20	1.40	1.95	3.85	5.70	6.25	6.40	7.60	9.35		200	1.20	4.20	5.80	22.05	76.50	6.10	12.05	19.80	42.15	91.65
	$S_{n,T}^{(3)}$	10	0.95	1.10	0.95	1.35	2.00	5.40	5.15	5.35	6.20	7.10	$J_{n,T}^{(3)}$	10		1.25	1.30	3.10	5.95		5.80	8.40	9.40	18.90
		20	0.75	1.65	1.50	1.50	2.55	5.30	5.50	5.60	6.35	8.15		20			1.80	2.40	7.30			7.00	9.40	22.95
		30	1.00	1.10	1.70	1.35	2.00	5.50	5.40	6.15	6.45	8.95		30				2.20	9.35				9.90	27.40
		50	0.95	1.35	1.50	1.60	2.40	5.30	5.85	6.05	7.15	8.30		50					12.45					30.55
		100	1.05	1.25	1.60	2.00	2.30	5.60	6.05	5.70	6.65	9.55		100										
		200	1.05	1.15	1.30	2.05	3.30	5.30	5.75	6.65	7.15	9.10		200										
Fixed	$S_{n,T}^{(4)}$	10	0.95	1.35	1.35	1.25	1.90	5.45	5.45	5.25	5.95	7.25	$J_{n,T}^{(4)}$	10	0.90	1.25	1.20	3.00	6.40	4.95	5.55	7.00	9.95	18.65
		20	1.10	0.95	1.45	1.15	2.00	5.55	5.80	5.50	6.20	7.60		20	0.90	1.55	1.80	2.65	9.10	4.60	6.25	8.10	11.35	24.85
		30	1.00	1.15	1.60	1.30	1.80	5.15	5.35	5.15	6.65	8.20		30	1.35	1.90	1.55	4.20	13.90	5.05	7.05	7.65	12.95	30.90
		50	0.75	0.75	1.60	1.15	2.70	4.90	5.00	5.80	6.70	7.90		50	0.95	1.10	3.05	4.60	20.45	5.10	8.10	9.30	14.70	43.25
		100	1.10	0.95	1.50	2.05	2.35	5.45	5.30	5.85	6.35	9.60		100	1.25	2.65	2.70	7.85	33.65	5.55	7.50	10.60	21.30	58.45
		200	1.35	1.10	1.30	1.70	3.15	5.80	5.80	6.25	7.95	9.30		200	1.75	2.15	2.60	11.00	53.95	5.65	9.15	10.90	28.25	76.15
Expanding	$S_{n,T}^{(4)}$	10	1.05	1.20	1.00	1.60	1.80	6.05	5.45	6.40	5.60	6.80	$J_{n,T}^{(4)}$	10	1.05	1.95	1.90	2.55	5.80	5.25	6.00	7.05	10.30	16.90
		20	1.10	0.95	1.45	1.15	2.00	5.55	5.80	5.50	6.20	7.60		20	0.90	1.55	1.80	2.65	9.10	4.60	6.25	8.10	11.35	24.85
		30	1.00	1.15	1.60	1.30	1.80	5.15	5.35	5.15	6.65	8.20		30	1.35	1.90	1.55	4.20	13.90	5.05	7.05	7.65	12.95	30.90
		50	0.75	0.75	1.60	1.15	2.70	4.90	5.00	5.80	6.70	7.90		50	0.95	1.10	3.05	4.60	20.45	5.10	8.10	9.30	14.70	43.25
		100	0.90	1.30	1.35	1.55	2.25	5.45	5.60	6.10	7.10	9.25		100	0.75	1.45	2.30	6.25	28.85	4.85	6.05	10.05	17.30	53.50
		200	1.10	0.95	1.55	1.55	3.30	4.85	5.65	6.70	7.90	9.25		200	1.35	2.25	3.35	9.45	47.15	4.15	6.60	9.40	21.65	68.50
Fixed	$S_{n,T}^{(5)}$	10	0.90	1.15	1.10	1.30	2.05	5.05	5.15	5.35	5.45	7.10	$J_{n,T}^{(5)}$	10	0.50	0.85	1.50	2.65	5.20	3.80	5.05	7.15	9.95	16.30
		20	0.90	0.90	1.60	1.20	1.95	5.35	5.65	5.70	6.00	7.85		20	0.70	0.50	0.50	2.30	8.15	3.05	3.45	5.70	10.25	23.95
		30	1.30	1.35	1.40	1.40	2.10	5.15	5.40	5.20	6.50	7.85		30	0.90	1.05	0.15	3.10	10.95	3.45	3.60	2.90	10.10	28.85
		50	0.80	0.90	1.85	1.50	2.65	4.90	5.45	6.35	6.95	8.00		50	0.55	0.60	0.30	2.45	18.75	3.85	2.65	3.95	12.95	40.60
		100	1.10	1.10	1.55	2.15	2.45	4.95	5.25	5.40	6.65	9.60		100	0.95	0.40	0.55	3.85	33.55	3.25	3.20	3.90	17.85	59.25
		200	1.25	1.25	1.50	1.75	3.85	5.35	5.80	6.50	7.50	9.65		200	0.60	0.30	1.20	0.70	41.65	2.45	2.75	3.80	4.40	66.90
Expanding	$S_{n,T}^{(5)}$	10	0.85	0.90	1.10	1.40	2.05	6.10	5.15	5.95	5.70	7.00	$J_{n,T}^{(5)}$	10	0.65	1.60	1.55	2.15	6.30	3.15	5.75	6.40	9.60	16.45
		20	0.90	0.90	1.60	1.20	1.95	5.35	5.65	5.70	6.00	7.85		20	0.70	0.50	0.50	2.30	8.15	3.05	3.45	5.70	10.25	23.95
		30	1.30	1.35	1.40	1.40	2.10	5.15	5.40	5.20	6.50	7.85		30	0.90	1.05	0.15	3.10	10.95	3.45	3.60	2.90	10.10	28.85
		50	0.80	0.90	1.85	1.50	2.65	4.90	5.45	6.35	6.95	8.00		50	0.55	0.60	0.30	2.45	18.75	3.85	2.65	3.95	12.95	40.60
		100	1.10	1.30	1.50	1.95	2.20	4.90	5.40	5.80	6.60	9.35		100	0.70	0.70	0.85	3.10	29.85	3.35	4.05	4.10	16.70	54.85
		200	1.40	1.10	1.50	1.85	3.55	4.90	5.80	6.55	7.45	9.25		200	0.60	0.75	0.40	0.45	33.15	2.80	2.20	2.30	3.45	58.35

Table 2.12: Size Adjusted Power Under Heterogeneous Alternative – DGP 2: Factor Dependence, Low Spatial Dependence

Overall EPA Test

Option	*Test*	$n \backslash T$	1% Nominal Size 10	20	30	50	100	5% Nominal Size 10	20	30	50	100
	$S_{n,T}^{(1)}$	10	1.05	1.15	1.15	1.00	1.10	5.20	5.10	5.40	5.00	5.65
		20	1.00	0.85	1.00	1.05	1.10	4.95	5.10	5.35	4.75	5.50
		30	1.05	0.95	0.95	0.90	1.30	5.05	4.90	5.10	5.00	5.10
		50	1.05	1.00	0.95	1.05	1.10	5.00	4.85	5.10	4.95	5.15
		100	0.95	1.05	0.95	1.00	1.15	5.10	5.05	5.15	5.20	5.05
		200	1.00	0.95	1.00	1.00	1.10	4.90	4.95	5.10	5.15	4.90
Truncated	$S_{n,T}^{(2)}$	10	0.95	1.10	1.10	0.85	1.05	5.45	5.10	5.25	4.95	6.05
		20	0.95	0.95	0.95	1.05	1.25	5.00	5.15	5.15	5.00	5.55
		30	1.00	0.90	1.15	0.95	1.25	5.15	5.00	5.35	5.10	5.30
		50	0.95	1.05	0.95	1.25	1.00	5.05	5.05	4.80	4.95	4.95
		100	0.90	1.05	1.05	0.95	1.10	4.95	5.05	5.20	5.05	5.25
		200	1.15	1.00	1.05	1.00	1.05	4.90	5.10	5.25	5.00	4.95
Bartlett	$S_{n,T}^{(2)}$	10	1.05	1.15	1.15	1.00	1.10	5.20	5.10	5.40	5.00	5.65
		20	0.90	1.00	0.90	1.00	1.10	4.90	5.35	5.15	5.20	5.65
		30	1.00	1.00	1.25	0.90	1.25	5.05	4.90	5.25	5.10	5.30
		50	1.05	1.15	1.15	1.20	1.10	5.10	5.10	5.00	4.90	5.05
		100	0.90	0.95	1.05	0.95	1.10	4.95	5.10	5.20	5.00	5.20
		200	1.00	1.15	1.05	1.05	1.00	4.85	4.95	5.20	5.10	5.00
Parzen	$S_{n,T}^{(2)}$	10	1.05	1.15	1.15	1.00	1.10	5.20	5.10	5.40	5.00	5.65
		20	1.00	1.00	0.95	1.05	1.10	5.10	5.05	5.20	5.15	5.65
		30	1.10	0.95	1.20	0.90	1.25	5.15	4.95	5.45	5.05	5.25
		50	0.95	1.05	1.00	1.15	1.15	5.15	5.15	4.80	4.95	5.15
		100	0.95	0.95	0.95	0.95	1.05	4.95	4.90	5.20	4.90	5.25
		200	1.00	1.00	1.05	1.05	1.05	4.85	4.90	5.15	5.00	4.95
Tukey	$S_{n,T}^{(2)}$	10	1.05	1.15	1.15	1.00	1.10	5.20	5.10	5.40	5.00	5.65
		20	0.95	1.00	0.90	0.95	1.05	4.90	5.20	5.10	5.20	5.65
		30	1.00	1.00	1.25	0.90	1.25	5.05	5.00	5.35	5.10	5.25
		50	1.05	1.10	1.15	1.20	1.10	5.00	5.15	4.95	4.90	5.10
		100	0.90	0.95	1.00	1.00	1.05	4.90	5.00	5.20	4.95	5.20
		200	1.00	1.10	1.05	1.05	1.00	5.05	4.95	5.15	5.15	5.05
QS	$S_{n,T}^{(2)}$	10	1.05	1.20	1.10	1.00	1.15	5.15	5.00	5.50	5.00	5.80
		20	0.90	0.95	0.95	1.05	1.20	4.95	5.25	5.10	5.20	5.55
		30	1.00	1.00	1.25	0.90	1.30	5.30	4.95	5.25	5.15	5.35
		50	1.00	1.05	1.05	1.20	1.10	5.00	5.00	4.90	4.90	5.00
		100	0.90	0.95	1.05	0.90	1.15	5.05	5.05	5.20	5.00	5.20
		200	1.05	1.10	1.05	1.05	1.00	4.90	5.05	5.20	5.05	5.00
	$S_{n,T}^{(3)}$	10	1.05	1.10	1.10	0.85	1.05	4.95	5.05	5.25	5.05	5.95
		20	0.95	0.90	1.00	1.00	1.20	5.10	5.15	5.20	5.05	5.70
		30	1.00	0.90	1.10	0.85	1.20	5.20	5.00	5.25	5.05	5.20
		50	0.95	1.05	1.00	1.20	0.95	5.00	5.15	5.00	4.70	4.95
		100	0.80	1.00	1.00	0.95	1.10	4.90	5.00	5.10	5.10	5.15
		200	0.95	1.05	1.00	0.95	1.05	4.90	5.20	5.00	4.90	4.90
Fixed	$S_{n,T}^{(4)}$	10	1.00	1.15	1.15	0.90	1.05	4.95	5.15	5.20	4.95	5.80
		20	0.95	0.90	1.05	1.10	1.20	5.00	5.15	5.15	5.10	5.75
		30	0.95	0.90	1.10	0.90	1.20	5.25	5.05	5.25	5.10	5.25
		50	0.95	1.05	1.00	1.20	0.95	5.00	5.15	5.00	4.75	4.95
		100	0.80	1.00	1.00	0.95	1.10	4.95	5.00	5.10	5.10	5.10
		200	0.95	1.05	1.00	0.95	1.05	4.90	5.20	5.00	4.90	4.90
Expanding	$S_{n,T}^{(4)}$	10	1.20	1.15	1.20	0.95	1.05	5.00	5.25	5.25	4.95	5.80
		20	0.95	0.90	1.05	1.10	1.20	5.00	5.15	5.15	5.10	5.75
		30	0.95	0.90	1.10	0.90	1.20	5.25	5.05	5.25	5.10	5.25
		50	0.95	1.05	1.00	1.20	0.95	5.00	5.15	5.00	4.75	4.95
		100	0.80	1.00	1.00	0.95	1.10	4.95	5.00	5.10	5.10	5.10
		200	0.95	1.05	1.00	0.95	1.05	4.90	5.20	5.00	4.90	4.90
Fixed	$S_{n,T}^{(5)}$	10	0.95	1.15	1.20	0.90	1.05	4.95	5.25	5.20	5.00	5.90
		20	0.95	0.90	0.95	1.05	1.20	4.90	5.05	5.15	5.15	5.80
		30	0.90	0.90	1.10	0.90	1.20	5.30	5.05	5.20	5.10	5.20
		50	0.95	1.05	1.00	1.20	0.95	4.95	5.15	4.90	4.75	4.95
		100	0.80	1.00	1.00	0.95	1.10	5.00	5.00	5.15	5.10	5.10
		200	0.95	1.05	1.00	0.95	1.05	4.90	5.20	5.10	4.90	4.90
Expanding	$S_{n,T}^{(5)}$	10	1.10	1.10	1.20	0.95	1.05	5.00	5.20	5.25	4.95	5.85
		20	0.95	0.90	0.95	1.05	1.20	4.90	5.05	5.15	5.15	5.80
		30	0.90	0.90	1.10	0.90	1.20	5.30	5.05	5.20	5.10	5.20
		50	0.95	1.05	1.00	1.20	0.95	4.95	5.15	4.90	4.75	4.95
		100	0.80	1.00	1.00	0.95	1.10	5.00	4.95	5.15	5.10	5.10
		200	0.95	1.05	1.00	0.95	1.05	4.90	5.20	5.10	4.90	4.90

Joint EPA Test

Option	*Test*	$n \backslash T$	1% Nominal Size 10	20	30	50	100	5% Nominal Size 10	20	30	50	100
	$J_{n,T}^{(1)}$	10	1.20	1.35	1.30	1.10	1.75	5.60	5.45	6.20	5.80	9.05
		20	1.05	1.15	1.10	1.20	1.50	5.30	5.80	5.95	6.15	8.50
		30	1.00	1.10	1.15	1.35	1.85	5.30	5.40	6.30	6.40	7.60
		50	0.95	1.10	1.45	1.35	1.70	5.30	5.45	5.80	6.30	7.75
		100	0.95	1.05	1.40	1.15	2.00	5.05	5.50	5.90	6.05	8.45
		200	1.15	1.25	1.15	1.20	1.75	5.35	5.60	5.80	5.80	8.55
Truncated	$J_{n,T}^{(2)}$	10	1.20	1.25	1.70	1.95	4.25	5.35	7.35	7.50	9.55	20.55
		20	0.40	0.60	0.75	0.60	1.45	2.85	3.45	5.60	5.30	9.55
		30	0.60	0.45	0.75	1.05	1.40	3.50	3.45	3.50	4.05	7.10
		50	0.70	0.75	1.20	1.15	1.65	3.25	4.00	4.15	5.85	7.35
		100	0.70	0.60	0.60	0.95	1.20	3.05	3.45	4.50	4.95	7.20
		200	0.85	0.50	0.65	1.10	1.35	3.50	3.10	3.70	4.75	6.75
Bartlett	$J_{n,T}^{(2)}$	10	1.20	1.35	1.30	1.10	1.75	5.60	5.45	6.20	5.80	9.05
		20	1.05	1.05	1.50	2.15	6.15	5.75	6.85	7.90	14.40	32.70
		30	0.95	1.35	1.60	2.70	6.40	5.95	7.80	8.10	12.95	31.95
		50	1.35	1.25	2.15	2.60	6.90	6.20	7.45	8.55	14.00	46.30
		100	1.35	2.10	2.90	3.35	35.70	6.70	9.35	13.20	23.35	86.70
		200	1.05	2.30	3.20	6.30	43.40	5.80	10.15	15.45	33.00	98.85
Parzen	$J_{n,T}^{(2)}$	10	1.20	1.35	1.30	1.10	1.75	5.60	5.45	6.20	5.80	9.05
		20	1.00	1.05	1.25	1.35	1.90	5.45	6.00	6.15	7.70	12.65
		30	1.00	1.10	1.55	1.50	3.10	5.60	6.05	6.90	7.65	11.15
		50	1.10	1.10	1.45	1.60	2.05	5.45	5.80	6.90	8.20	13.00
		100	1.05	1.35	1.90	2.05	12.15	6.15	6.90	10.05	11.50	50.15
		200	1.10	2.05	1.75	3.05	7.70	5.70	8.40	10.25	16.05	70.45
Tukey	$J_{n,T}^{(2)}$	10	1.20	1.35	1.30	1.10	1.75	5.60	5.45	6.20	5.80	9.05
		20	0.90	1.15	1.65	2.20	6.90	5.10	7.70	7.75	15.00	34.30
		30	0.95	1.45	1.40	2.95	7.65	5.50	7.95	9.15	13.30	37.50
		50	1.00	1.20	1.85	2.45	6.25	6.05	8.00	9.25	15.35	50.05
		100	0.70	2.60	4.20	5.35	66.50	6.10	11.75	21.45	41.30	97.00
		200	0.75	1.55	4.25	12.15	86.50	5.05	11.50	23.65	59.75	100.00
QS	$J_{n,T}^{(2)}$	10	1.10	1.35	1.40	1.10	1.90	5.60	5.65	6.15	6.40	10.55
		20	1.10	1.20	1.70	5.55	21.85	6.45	9.10	13.40	27.85	59.20
		30	1.10	1.75	2.45	5.65	28.25	6.00	10.45	13.45	27.80	67.15
		50	1.40	1.50	3.60	6.35	35.55	7.05	9.80	13.15	31.25	85.15
		100	1.65	3.50	5.75	13.40	91.65	7.90	14.75	33.50	64.80	99.80
		200	1.35	2.65	7.20	35.55	99.05	7.45	17.90	40.85	86.00	100.00
	$J_{n,T}^{(3)}$	10		2.30	7.20	18.70	56.75		12.45	22.65	38.25	75.90
		20			5.10	25.20	77.45			17.45	48.75	91.45
		30				19.05	86.35				44.95	96.00
		50					89.95					97.75
		100										
		200										
Fixed	$J_{n,T}^{(4)}$	10	1.35	2.35	4.35	13.50	44.55	5.80	12.10	16.85	34.05	68.05
		20	1.90	4.15	7.35	18.10	67.25	7.60	13.80	21.45	45.05	83.75
		30	1.40	6.00	9.70	30.10	83.25	9.60	15.95	29.20	58.90	94.85
		50	2.30	8.25	12.95	50.80	94.10	8.80	21.15	36.60	76.20	98.80
		100	3.10	12.60	28.50	74.95	100.00	11.70	31.60	54.25	90.60	100.00
		200	4.35	24.60	54.30	95.80	100.00	13.35	44.35	74.05	98.85	100.00
Expanding	$J_{n,T}^{(4)}$	10	1.65	2.70	3.50	6.65	23.80	7.40	9.95	14.30	22.60	55.90
		20	1.90	4.15	7.35	18.10	67.25	7.60	13.80	21.45	45.05	83.75
		30	1.40	6.00	9.70	30.10	83.25	9.60	15.95	29.20	58.90	94.85
		50	2.30	8.25	12.95	50.80	94.10	8.80	21.15	36.60	76.20	98.80
		100	1.20	6.20	17.95	57.85	98.70	6.05	19.65	37.85	78.45	99.90
		200	1.85	9.25	22.60	56.20	85.60	6.70	20.80	38.45	68.25	89.05
Fixed	$J_{n,T}^{(5)}$	10	0.20	1.00	4.35	14.35	48.20	5.00	8.90	16.90	35.40	71.70
		20	0.45	0.45	0.85	1.30	10.40	2.95	2.80	6.00	9.95	77.70
		30	0.65	0.55	0.80	1.30	70.30	3.95	3.45	4.35	13.85	95.40
		50	0.80	0.70	0.75	1.20	98.50	3.30	3.60	3.60	13.40	99.80
		100	0.60	0.70	0.55	0.60	100.00	3.00	4.30	2.80	19.30	100.00
		200	0.45	0.70	0.40	1.10	99.85	2.20	3.10	3.65	5.85	99.85
Expanding	$J_{n,T}^{(5)}$	10	0.45	0.55	0.60	6.45	32.95	2.95	7.25	13.60	27.55	64.80
		20	0.45	0.45	0.85	1.30	10.40	2.95	2.80	6.00	9.95	77.70
		30	0.65	0.55	0.80	1.30	70.30	3.95	3.45	4.35	13.85	95.40
		50	0.80	0.70	0.75	1.20	98.50	3.30	3.60	3.60	13.40	99.80
		100	0.45	0.35	0.35	1.05	99.95	2.65	2.90	1.75	29.10	100.00
		200	0.25	0.80	0.55	0.50	77.65	1.40	3.10	2.95	3.20	85.95

Chapter 3

Multistep Forecasts with Factor-Augmented Panel Regressions

In two previous chapters two different questions on prediction were considered using panel data sets. In this chapter, we focus on an empirical investigation of the optimal forecasting strategy in a macroeconomic panel dataset. We compare the iterated and direct forecasts in a panel data context combining them with methods built specifically for panels with common factors. Using a quarterly dataset containing seventeen quarterly macroeconomic variables in OECD countries, we show that the direct forecasts based on a horizon specific model which uses multistep ahead values of the dependent variable with respect to the right hand side variables outperform the iterated forecasts made by a 1-step ahead model iterated until the horizon of interest. The results show that the methods which involve global common factors perform significantly better than the ones which use only country-specific information.

3.1 Introduction

The optimal forecasts for a single time series are well documented. Available methods include dynamic time series methods such as autoregressive moving average models; multivariate methods like vector autoregressions; nonlinear models, for instance threshold autoregressive models or regime switching models. If the interest lies on multistep ahead forecasts, regardless of the model of choice, the practitioner has to choose between two competing methods of forecasting: the iterated forecasts which are made by a 1-step ahead model iterated until the horizon of interest, and the direct forecasts which are based on a horizon specific model using multistep ahead values of the dependent variable with respect to the right hand side variables. The literature comparing the two strategies in a time series context is large. Whereas for panel data, no study has ever been conducted.

In this chapter, we investigate the optimal forecasting strategy using a family of dynamic heterogeneous panel predictive regression models. The general model under consideration allows us to predict unit specific outcomes with global common factors in macroeconomic variables. The main aim of the chapter is to propose and compare forecast methods using such panels with unobserved common factors. We compare empirical iterated and direct forecasts using two different approaches developed for panels with common factors. The first one uses estimates of the common factors in the predictive model by applying principal components analysis (PCA) on the residuals from a first stage consistent estimation. The unobserved nature of the common factors requires forecasting the future values of these estimated factors first, then computing the predictions on the variable of interest in a following step. In the second approach, the common factors are estimated from a number of auxiliary variables as in the works of Stock and Watson (2002a) and Bai and Ng (2006). The difference between these studies and ours is that in our study common factors are estimated from the realizations of the same variable for different panel units whereas in their studies these factors come from a large number of indicators for the same panel unit. Although, our approach does not rule out the possibility of having several variables correlated with the common factors.

Another aim of the chapter is to reconsider the question of pooling time series in the presence of cross-sectional dependence (CD). In forecasting studies for a time series, estimation method is of secondary interest. Whereas in panel data practitioner can choose between using unit specific estimates of the slope parameters or pooled estimates which impose homogeneity on them. The optimal strategy depends on the particular dataset and model, hence it is an empirical matter. Theoretically, pooling in heterogeneous panels can produce misleading results on the magnitude of the average effects and inference based on them (Baltagi et al., 2008; Pesaran and Smith, 1995). However, when the estimates of the individual parameters contain too much noise, pooling can provide better out-of-sample forecasts (Mark and Sul, 2012). We investigate the role of CD on the optimal prediction strategy.

The final aim is to compare estimators recently proposed in the literature for panels containing unobserved common factors. We use methods by Pesaran (2006), Bai (2009), Song (2013) and related estimators for the slope parameters and compare their small sample performance in terms of prediction accuracy.

The chapter contributes to the literature on forecasting with panel data in several dimensions. First, we empirically investigate the role of using global information by means of estimates of common factors, on forecasting country specific series. We compare forecasts of two inflation series observed in quarterly frequency from early 1990s for 24 OECD countries. This corresponds to comparing the forecasts of 48 time series in total. Second, we compare direct and iterated multistep forecasting methods by considering specific challenges arising from using panel data, namely heterogeneity and CD. Finally, we contribute to the literature comparing different panel data estimators in terms of predictive performance in an empirical context.

The plan of the chapter is as follows. In Section 3.2, we introduce the general panel predictive model, the two approaches of forecasting with unobserved common factors in the context of iterated and direct forecast methods. In Section 3.3 parameter estimation methods and model selection criteria are described. Section 3.4 contains the empirical application. In this section the dataset is introduced, its time series and cross-section properties are investigated and the results on out-of-sample forecasts are discussed. Section 3.5 concludes.

3.2 Models and Forecasting Approaches

In this section, we introduce the general dynamic heterogeneous panel predictive regression model which nests the models regularly used in macroeconomic forecasting studies. Also the direct and iterated methods of prediction are described in the panel data context with special emphasis on using global factors to forecast country specific variables.

3.2.1 Models

Our purpose is to make multistep ahead forecasts of the dependent variable $\widehat{y}_{it}$. These forecasts are denoted by

$$\widehat{y}_{i,t+h|t} = g(\mathbf{h}_{it}, \widetilde{\mathbf{f}}_t, \widehat{\boldsymbol{\theta}}_i),$$

where $h = 1, \ldots, P$ is the forecast horizon, $i = 1, 2, \ldots, n$ denote the panel units observed for the time period $t = \ldots, 1, 2, \ldots, T$, $g(\cdot)$ is a linear function, $\mathbf{h}_{it}$ is a vector of observable variables, $\widetilde{\mathbf{f}}_t$ is a vector containing estimates of unobservables $\mathbf{f}_t$, and $\widehat{\boldsymbol{\theta}}_i$ is a vector of estimated parameters. For this purpose we consider several different panel predictive regression models and prediction methods.

The most general model that we consider is a factor augmented panel autoregressive distributed lag model, denoted FARDL(p, q). It is given by

$$y_{i,t+h} = \alpha_i + \sum_{l=1}^{p} \rho_{li} y_{i,t+1-l} + \sum_{l=1}^{q} \boldsymbol{\delta}'_{li} \mathbf{x}_{i,t+1-l} + \boldsymbol{\gamma}'_i \mathbf{f}_t + u_{i,t+h}, \tag{3.1}$$

where α_i are the country fixed effects which are treated as parameters to be estimated, ρ_{li}, $l = 1, 2, \ldots, p$, are autoregressive parameters, $\mathbf{x}_{it} = (x_{i1t}, x_{i2t}, \ldots, x_{ikt})'$ is a $(k \times 1)$ vector of observed, country specific indicators and $\boldsymbol{\delta}_{li} = (\delta_{l1i}, \delta_{l2i}, \ldots, \delta_{lki})'$, $l = 1, 2, \ldots, p$, represent the corresponding $(k \times 1)$ parameters to be estimated, $\mathbf{f}_t = (f_{1t}, f_{2t}, \ldots, f_{mt})'$ is an $(m \times 1)$ vector of unobserved common factors, $\boldsymbol{\gamma}_i = (\gamma_{i1}, \gamma_{i2}, \ldots, \gamma_{im})'$ is the associated $(m \times 1)$ vector of factor loadings, u_{it} are the error terms which are assumed to be serially uncorrelated but allowed to be cross-sectionally weakly correlated.

The vector $\mathbf{x}_{it}$ contains observable variables which are thought to be able to contribute to the prediction of the variable of interest. These can be the variables which are assumed to be in the generating process of the dependent variable y_{it} or any leading indicator which improves the prediction $\widehat{y}_{it}$.

The model in (3.1) can be written compactly as

$$y_{i,t+h} = \alpha_i + \boldsymbol{\beta}_i'\mathbf{h}_{it} + \boldsymbol{\gamma}_i'\mathbf{f}_t + u_{i,t+h}, \tag{3.2}$$

where $i = 1, 2, \ldots, n$, $t = 1, 2, \ldots, T$ and $\mathbf{h}_{it} = (y_{it}, \ldots, y_{i,t-p+1}, \mathbf{x}_{it}', \ldots, \mathbf{x}_{i,t-q+1}')'$, $\boldsymbol{\beta}_i = (\rho_{1i}, \ldots, \rho_{pi}, \boldsymbol{\delta}_{1i}', \ldots, \boldsymbol{\delta}_{qi}')'$. In the empirical exercise below, we use different models nested in this general model. First one is an AR(p) model obtained by setting $\boldsymbol{\delta}_{li} = 0$ for all $i = 1, 2, \ldots, n$ and $l = 1, 2, \ldots, p$, and $\boldsymbol{\gamma}_i'\mathbf{f}_t = 0$ for all $i = 1, 2, \ldots, n$ and $t = 1, 2, \ldots, T$. Second one is an ARDL(p, q), obtained under $\boldsymbol{\gamma}_i'\mathbf{f}_t = 0$ for all $i = 1, 2, \ldots, n$ and $t = 1, 2, \ldots, T$. Third one is a factor-augmented autoregressive model, FAR(p), given by the constraints $\boldsymbol{\delta}_{li} = 0$ for all $i = 1, 2, \ldots, n$ and $l = 1, 2, \ldots, p$. Finally, we use the general FARDL(p, q) model. In addition, for each model we make predictions under the homogeneity assumption $\boldsymbol{\beta}_i = \boldsymbol{\beta}$. Throughout the chapter we use the heterogeneous notation but it should be understood that under the homogeneity assumption we replace both population parameters and their estimates with homogeneous versions.

3.2.2 Forecasting Approaches

It is known that when the 1-step ahead model is correctly specified, the iterated forecasts are efficient (Bhansali, 2002). However, if the model is not correctly specified, or the data shows evidence of non-stationarity, these forecasts are not optimal, whereas direct methods are so (Marcellino et al., 2006). Especially in a panel data context where heterogeneity among units make it difficult to choose an overall correctly specified model, the direct forecast method becomes attractive. However, as theoretical knowledge on the optimal strategy is incomplete, the best strategy is an empirical matter. In the following subsections we introduce the direct and iterated forecast methods using panel data.

3.2.2.1 Direct Forecasts

Direct forecasts are made by estimating the h-steps ahead model (3.2), that is, the dependent variable is the h-steps ahead value with respect to the right hand side variables. In the case of models without common factors, namely AR(p) and ARDL(p, q), the prediction procedure is straightforward. The direct predictions in time period $T + h$ are computed as

$$\widehat{y}^{D}_{i,T+h|T} = \widehat{\alpha}_i + \widehat{\boldsymbol{\beta}}_i{}' \mathbf{h}_{iT}.$$

Prediction using factor augmented models FAR(p) and FARDL(p, q) is less straightforward as they include unobservable common factors $\mathbf{f}_t$. In the case of direct method of forecasting, the predictions which replace the unobserved common factors with their estimates are given by

$$\widehat{y}^{D}_{i,T+h|T} = \widehat{\alpha}_i + \widehat{\boldsymbol{\beta}}_i' \mathbf{h}_{iT} + \widehat{\boldsymbol{\gamma}}_i' \widetilde{\mathbf{f}}_T,$$

where $\widetilde{\mathbf{f}}_T$ is an estimate of the unobservable common factors $\mathbf{f}_T$. The main issue is that the unobservable common factors have to be estimated from the data. We use two different approaches, called the Residual Based Approach (RBA) and the Auxiliary Variables Approach (AVA) which are described below.

Direct Forecasts by the Residual Based Approach

Step 1: Estimate (3.2) using any estimator which controls for unobserved common factors as described in the next section and compute the residuals

$$\widehat{e}_{it} = y_{it} - \widehat{\alpha}_i - \widehat{\boldsymbol{\beta}}_i' \mathbf{h}_{i,t-h}, \quad t = h+1, \ldots, T,$$

where $\widehat{\boldsymbol{\beta}}_i$ is a consistent estimate of $\boldsymbol{\beta}_i$ and

$$\widehat{\alpha}_i = \frac{1}{T-h} \sum_{t=h+1}^{T} \left(y_{it} - \widehat{\boldsymbol{\beta}}_i' \mathbf{h}_{i,t-h} \right).$$

Step 2: Using PCA on the residuals $\widehat{e}_{it}$, $t = h+1, \ldots, T$, estimate $\mathbf{f}_t$ denoted $\widehat{\mathbf{f}}_t$, $t = h+1, \ldots, T-h$, and compute the factor loadings estimate $\widehat{\boldsymbol{\gamma}}_i$.

Step 3: Using the estimates $\widehat{\mathbf{f}}_t$, $t = h+1, \ldots, T-h$, predict the h-steps ahead values $\widetilde{\mathbf{f}}_T^D$ using the direct approach.

Step 4: Compute the prediction in time $T+h$ as

$$\widehat{y}_{i,T+h|T}^{D,R} = \widehat{\alpha}_i + \widehat{\boldsymbol{\beta}}_i' \mathbf{h}_{iT} + \widehat{\boldsymbol{\gamma}}_i' \widetilde{\mathbf{f}}_T^D .$$

Alternatively, we can assume that some auxiliary variables $\mathbf{w}_{it}$ are observable which satisfy

$$\mathbf{w}_{it} = \mathbf{a}_i + \boldsymbol{\Gamma}_i' \mathbf{f}_t^w + \boldsymbol{\varsigma}_{it}, \quad t = 1, \ldots, T, \tag{3.3}$$

such that $\mathbf{f}_t \subseteq \mathbf{f}_t^w$, where $\mathbf{w}_{it} = (w_{i1t}, w_{i2t}, \ldots, w_{ik_wt})'$ is a $(k_w \times 1)$ vector of observed individual-specific variables, $\mathbf{a}_i$ are the fixed effects, $\boldsymbol{\Gamma}_i$ is the $(m_w \times k_w)$ matrix of factor loadings associated with the $(m_w \times 1)$ unobservable common factors $\mathbf{f}_t^w$. Note that $\mathbf{w}_{it}$ can contain $\mathbf{h}_{it}$ as its components. Then the prediction methodology, which we call Auxiliary Variables Approach (AVA), is based on the following four steps:

Direct Forecasts by the Auxiliary Variables Approach

Step 1: Estimate (3.2) using any estimator which controls for unobserved common factors as described in the next section and compute the residuals

$$\widehat{e}_{it} = y_{it} - \widehat{\alpha}_i - \widehat{\boldsymbol{\beta}}_i' \mathbf{h}_{i,t-h}, \quad t = h+1, \ldots, T,$$

where $\widehat{\boldsymbol{\beta}}_i$ is a consistent estimate of $\boldsymbol{\beta}_i$ and

$$\widehat{\alpha}_i = \frac{1}{T-h} \sum_{t=h+1}^{T} \left(y_{it} - \widehat{\boldsymbol{\beta}}_i' \mathbf{h}_{i,t-h} \right).$$

Step 2: Using PCA on the variables $\mathbf{w}_{it}$, $t = 1, \ldots, T$, estimate $\mathbf{f}_t^w$, denoted $\widetilde{\mathbf{f}}_t^w$, $t = 1, \ldots, T$.

Step 3: Estimate the factor loadings $\widehat{\boldsymbol{\gamma}}_i^w$ by OLS on the regression

$$\widehat{e}_{it} = \boldsymbol{\gamma}_i^w \widehat{\mathbf{f}}_{t-h}^w + \nu_{it}, \quad t = h+1, \ldots, T.$$

Step 4: Compute the prediction in time $T+h$ as

$$\widehat{y}_{i,T+h|T}^{D,A} = \widehat{\alpha}_i + \widehat{\boldsymbol{\beta}}_i' \mathbf{h}_{iT} + \widehat{\boldsymbol{\gamma}}_i^{w\prime} \widehat{\mathbf{f}}_T^w.$$

3.2.2.2 Iterated Forecasts

To perform the iterated predictions we start by estimating a 1-step ahead model, namely the model (3.2) with $h = 1$, as $y_{i,t+1} = \alpha_i + \boldsymbol{\beta}_i' \mathbf{h}_{it} + \boldsymbol{\gamma}_i' \mathbf{f}_t + u_{i,t+1}$. After the estimation of this model, h-steps ahead forecasts are computed by recursive estimation of the parameters. For the models without common factors, AR(p) and ARDL(p,q), the forecasts are given by

$$\widehat{y}_{i,T+h|T}^{I} = \widehat{\alpha}_i + \widehat{\boldsymbol{\beta}}_i' \widehat{\mathbf{h}}_{i,T+h-1|T}^{I}.$$

The iterated forecasts for the models FAR(p) and FARDL(p,q) are constructed similarly to the ones above by

$$\widehat{y}_{i,T+h|T}^{I} = \widehat{\alpha}_i + \widehat{\boldsymbol{\beta}}_i' \widehat{\mathbf{h}}_{i,T+h-1|T}^{I} + \widehat{\boldsymbol{\gamma}}_i' \widetilde{\mathbf{f}}_{T+h-1|T}^{I}.$$

Once more, the main question is how to form the estimates of the unobservable common factors. The iterated forecasts with the RBA and the AVA are described in what follows.

Iterated Forecasts by the Residual Based Approach

Step 1: Set $s = 0$.

Step 2: Using any estimator which controls for unobserved common factors as described in the next section, estimate

$$\widehat{y}_{it}^{I,R} = \alpha_i + \boldsymbol{\beta}_i' \widehat{\mathbf{h}}_{i,t-1}^{I} + e_{it}$$

where $\widehat{y}_{it}^{I,R} = y_{it}$ and $\widehat{\mathbf{h}}_{it}^{I} = \mathbf{h}_{it}$ if $s = 0$, and compute the residuals

$$\widehat{e}_{it} = \widehat{y}_{it}^{I,R} - \widehat{\alpha}_i - \widehat{\boldsymbol{\beta}}_i' \widehat{\mathbf{h}}_{i,t-1}^{I}, \quad t = 2, \ldots, T+s,$$

where $\widehat{\boldsymbol{\beta}}_i$ is a consistent estimate of $\boldsymbol{\beta}_i$ and

$$\widehat{\alpha}_i = \frac{1}{T+s-1} \sum_{t=2}^{T+s} \left(\widehat{y}_{it}^{I,R} - \widehat{\boldsymbol{\beta}}_i' \widehat{\mathbf{h}}_{i,t-1}^{I} \right).$$

Step 3: Using PCA on the residuals $\widehat{e}_{it}$, $t = 2, \ldots, T+s$, estimate $\mathbf{f}_t$ denoted $\widehat{\mathbf{f}}_t$, $t = 2, \ldots, T+s-1$, and compute the factor loadings estimate $\widehat{\boldsymbol{\gamma}}_i$.

Step 4: Using the estimates $\widehat{\mathbf{f}}_t$, $t = 2, \ldots, T+s-1$, predict the 1-step ahead value $\widetilde{\mathbf{f}}_{T+s}$.

Step 5: If $s \neq 0$, predict the 1-step ahead value $\widehat{\mathbf{h}}_{i,T+s}^{I}$.

Step 6: Compute the prediction in time $T+s+1$ as

$$\widehat{y}_{i,T+s+1|T}^{I,R} = \widehat{\alpha}_i + \widehat{\boldsymbol{\beta}}_i' \widehat{\mathbf{h}}_{i,T+s}^{I} + \widehat{\boldsymbol{\gamma}}_i' \widetilde{\mathbf{f}}_{T+s}^{I}.$$

Step 7: Set $s = s+1$ and repeat steps 2-6 until $s+1 = h$.

It is possible to make iterated forecasts using the AVA, assuming that some auxiliary variables containing the common factors exist. The steps of the iterated forecasts using the AVA is given below.

Iterated Forecasts by the Auxiliary Variables Approach

Step 1: Set $s = 0$.

Step 2: Using PCA on the variables $\mathbf{w}_{it}$, $t = 1, \ldots, T$, estimate $\mathbf{f}_t^w$, denoted $\widetilde{\mathbf{f}}_t^w$, $t = 1, \ldots, T$.

Step 3: Estimate

$$\widehat{y}_{i,t+1}^{I,R} = \alpha_i + \boldsymbol{\beta}_i' \widehat{\mathbf{h}}_{it}^{I} + e_{i,t+1}$$

using any estimator which controls for unobserved common factors as described in the next section and compute the residuals

$$\widehat{e}_{it} = \widehat{y}_{i,t+1}^{I,R} - \widehat{\alpha}_i - \widehat{\boldsymbol{\beta}}_i' \widehat{\mathbf{h}}_{it}^{I}, \quad t = 2, \ldots, T+s,$$

where $\widehat{\boldsymbol{\beta}}_i$ is a consistent estimate of $\boldsymbol{\beta}_i$ and

$$\widehat{\alpha}_i = \frac{1}{T+s-1}\sum_{t=2}^{T+s}\left(\widehat{y}_{i,t+1}^{I,R} - \widehat{\boldsymbol{\beta}}_i'\widehat{\mathbf{h}}_{it}^{I}\right).$$

Step 4: Predict the 1-step ahead value $\widetilde{\mathbf{f}}_{T+s}^{w,I}$ and if $s \neq 0$, predict also the 1-step ahead value $\widehat{\mathbf{h}}_{i,T+s}^{I}$.

Step 5: Estimate the factor loadings $\widehat{\boldsymbol{\gamma}}_i^w$ by *OLS* on the regression

$$\widehat{e}_{it} = \boldsymbol{\gamma}_i^w \widetilde{\mathbf{f}}_{t-1}^{w,I} + \nu_{it}, \quad t = 2, \ldots, T+s.$$

Step 6: Compute the prediction in time $T+s+1$ as

$$\widehat{y}_{i,T+s+1|T}^{I,A} = \widehat{\alpha}_i + \widehat{\boldsymbol{\beta}}_i'\widehat{\mathbf{h}}_{i,T+s}^{I} + \widehat{\boldsymbol{\gamma}}_i^{w\prime}\widetilde{\mathbf{f}}_{T+s}^{w,I}.$$

Step 7: Set $s = s+1$ and repeat steps 3-6 until $s+1 = h$.

3.3 Estimation and Model Selection

We use several different estimators of the slope parameters $\boldsymbol{\beta}_i$, or, when homogeneity is assumed, of $\boldsymbol{\beta}$. First, as the properties of the underlying conditional expectation function are unknown in terms of heterogeneity, we implement and compare heterogeneous and homogeneous estimators of the slope parameters. In the cases of heterogeneity, we assume that the slope coefficients $\boldsymbol{\beta}_i$ follow the random coefficient model

$$\boldsymbol{\beta}_i = \boldsymbol{\beta} + \boldsymbol{\Delta}_i, \quad \boldsymbol{\Delta}_i \sim \mathrm{IID}(\mathbf{0}, \boldsymbol{\Omega}_\Delta), \tag{3.4}$$

where $\boldsymbol{\beta} = (\rho_1, \ldots, \rho_p, \boldsymbol{\delta}_1', \ldots, \boldsymbol{\delta}_q')'$, $\boldsymbol{\Delta}_i$ is a vector of random variables distributed independently of other random components of the model.

Second, to compute the predictions which involve unobserved common factors, we use estimators which are robust to correlations between these unobserved components and the right hand side variables. In Section 3.3.1 estimation methods which do not control for common factors, whereas in Section 3.3.2 methods which are robust to unobserved common factors are described.

3.3.1 Estimators with No Common Factors

When, in model (3.2), it is assumed that $\boldsymbol{\gamma}_i'\mathbf{f}_t = 0$ we use estimators which do not control for unobserved common factors. Let us define the matrices of deviations from the means as $\widetilde{\mathbf{H}}_{i.,-h} = \mathbf{M}_e\mathbf{H}_{i.,-h}$, $\tilde{\mathbf{y}}_{i.} = \mathbf{M}_e\mathbf{y}_{i.}$, $\mathbf{H}_{i.,-h} = (\mathbf{h}_{i1}', \mathbf{h}_{i2}', \dots, \mathbf{h}_{i,T-h}')'$, $\mathbf{y}_{i.} = (y_{i,h+1}, y_{i2}, \dots, y_{iT})'$ and $\mathbf{M}_e = \mathbf{I}_{T-h} - (T-h)^{-1}\mathbf{e}_{T-h}\mathbf{e}_{T-h}'$, where $\mathbf{e}_{T-h}$ is a vector of ones of length $T-h$. The *OLS* estimator of the unit specific intercepts is given by

$$\widehat{\boldsymbol{\beta}}_{OLS,i} = \left(\widetilde{\mathbf{H}}_{i.,-h}'\widetilde{\mathbf{H}}_{i.,-h}\right)^{-1}\widetilde{\mathbf{H}}_{i.,-h}'\tilde{\mathbf{y}}_{i.}. \tag{3.5}$$

Conditional on $\boldsymbol{\beta}_i$, the *OLS* estimator is the best linear unbiased predictor (BLUP) of the random coefficient $\boldsymbol{\beta}_i$ under the assumption of no cross-sectional dependence. Lee and Griffiths (1979) show that, unconditionally, the feasible BLUP of $\boldsymbol{\beta}_i$ is given by

$$\widehat{\boldsymbol{\beta}}_{GLS,i} = \widehat{\boldsymbol{\beta}}_{SW} + \widehat{\boldsymbol{\Omega}}_\Delta\widetilde{\mathbf{H}}_{i.,-h}'\left(\widehat{\sigma}_i^2\mathbf{I}_{T-h} + \widetilde{\mathbf{H}}_{i.,-h}\widehat{\boldsymbol{\Omega}}_\Delta\widetilde{\mathbf{H}}_{i.,-h}'\right)^{-1}\left(\tilde{\mathbf{y}}_{i.} - \widetilde{\mathbf{H}}_{i.,-h}\widehat{\boldsymbol{\beta}}_{SW}\right), \tag{3.6}$$

where $\widehat{\boldsymbol{\beta}}_{SW}$ is the feasible *GLS* estimator of the average coefficients $\boldsymbol{\beta}$ derived by Swamy (1970) as

$$\widehat{\boldsymbol{\beta}}_{SW} = \sum_{i=1}^{n}\mathbf{W}_i\widehat{\boldsymbol{\beta}}_{OLS,i},$$

$$\mathbf{W}_i = \left[\sum_{j=1}^{n}\left(\widehat{\boldsymbol{\Omega}}_\Delta + \widehat{\boldsymbol{\Sigma}}_{\widehat{\beta}_{OLS,j}}\right)^{-1}\right]^{-1}\left(\widehat{\boldsymbol{\Omega}}_\Delta + \widehat{\boldsymbol{\Sigma}}_{\widehat{\beta}_{OLS,i}}\right)^{-1},$$

with $\widehat{\boldsymbol{\Sigma}}_{\widehat{\beta}_{OLS,i}} = \widehat{\sigma}_i^2\left(\widetilde{\mathbf{H}}_{i.,-h}'\widetilde{\mathbf{H}}_{i.,-h}\right)^{-1}$, $\widehat{\sigma}_i^2 = \frac{1}{T-h}\widehat{\mathbf{e}}_{i.}'\widehat{\mathbf{e}}_{i.}$, $\widehat{\mathbf{e}}_{i.} = \tilde{\mathbf{y}}_{i.} - \widetilde{\mathbf{H}}_{i.,-h}\widehat{\boldsymbol{\beta}}_{OLS,i}$ and $\widehat{\boldsymbol{\Omega}}_\Delta = \frac{1}{n-1}\sum_{i=1}^{n}\left(\widehat{\boldsymbol{\beta}}_i - \widehat{\boldsymbol{\beta}}_{MG}\right)\left(\widehat{\boldsymbol{\beta}}_i - \widehat{\boldsymbol{\beta}}_{MG}\right)'$.

In the case of the homogeneity assumption we use two estimators of the average coefficients. First one is the usual fixed effects (*FE*) estimator based on within transformation, given by

$$\widehat{\boldsymbol{\beta}}_{FE} = \left(\sum_{i=1}^{n} \widetilde{\mathbf{H}}'_{i.,-h}\widetilde{\mathbf{H}}_{i.,-h}\right)^{-1} \sum_{i=1}^{n} \widetilde{\mathbf{H}}'_{i.,-h}\widetilde{\mathbf{y}}_{i.}. \tag{3.7}$$

Alternatively, Chamberlain (1982) and Pesaran and Smith (1995) suggest estimating the average coefficient vector $\boldsymbol{\beta}$ by the mean group (MG) estimator as

$$\widehat{\boldsymbol{\beta}}_{MG} = n^{-1} \sum_{i=1}^{n} \widehat{\boldsymbol{\beta}}_{OLS,i}. \tag{3.8}$$

Under general conditions, the assumption $\boldsymbol{\gamma}'_i \mathbf{f}_t = 0$ and that the explanatory variables are strictly exogeneous, $\widehat{\boldsymbol{\beta}}_{OLS,i}$ is consistent for $\boldsymbol{\beta}_i$ as $T \to \infty$ and $\widehat{\boldsymbol{\beta}}_{MG}$, $\widehat{\boldsymbol{\beta}}_{SW}$ and $\widehat{\boldsymbol{\beta}}_{FE}$ are consistent for $\boldsymbol{\beta}$ as $n, T \to \infty$. If the explanatory variables contain weakly exogenous regressors, Pesaran and Smith (1995) show that $\widehat{\boldsymbol{\beta}}_{FE}$ is inconsistent in the case of heterogeneous slope parameters.

3.3.2 Estimators with Common Factors

If, in model (3.2), $\boldsymbol{\gamma}'_i \mathbf{f}_t \neq 0$ the estimators in previous subsection are inconsistent for the parameters of the right hand side variables. To control for unobserved common factors, Pesaran (2006) proposes to use the cross-sectional averages of the dependent variable and the independent variables as proxies for these unobserved common factors. The estimator for the individual parameters is given by

$$\widehat{\boldsymbol{\beta}}_{CCE,i} = \left(\mathbf{H}'_{i.,-h}\mathbf{M}_{G_1}\mathbf{H}_{i.,-h}\right)^{-1} \mathbf{H}'_{i.,-h}\mathbf{M}_{G_1}\mathbf{y}_{i.}, \tag{3.9}$$

where $\mathbf{M}_{G_1} = \mathbf{I}_{T-h} - \mathbf{G}_1(\mathbf{G}'_1\mathbf{G}_1)^{-}\mathbf{G}'_1$, $\mathbf{G}_1 = (\mathbf{e}_{T-h}, \bar{\mathbf{Z}})$, $\bar{\mathbf{Z}} = (\bar{\mathbf{z}}'_{.1}, \bar{\mathbf{z}}'_{.2}, \ldots, \bar{\mathbf{z}}'_{.,T-h})'$, $\bar{\mathbf{z}}'_{.t} = n^{-1}\sum_{i=1}^{n} \mathbf{z}'_{it}$ and $\mathbf{z}_{it} = (y_{it}, \mathbf{x}'_{i,t-h})'$, $t = h+1, \ldots, T$. In general, one can use cross-sectional averages of any set of variables correlated with the common factors.

Song (2013) considers an iterative PC estimator of the individual parameters, based on the pooled estimator of Bai (2009). This estimator is defined by the following two nonlinear equations:

$$\widehat{\boldsymbol{\beta}}_{IPC,i} = \left(\mathbf{H}'_{i.,-h}\mathbf{M}_{G_2}\mathbf{H}_{i.,-h}\right)^{-1}\mathbf{H}'_{i.,-h}\mathbf{M}_{G_2}\mathbf{y}_{i.}, \tag{3.10}$$

$$\left[\frac{1}{nT}\sum_{i=1}^{n}\left(\mathbf{y}_{i.} - \mathbf{H}_{i.,-h}\widehat{\boldsymbol{\beta}}_{IPC,i}\right)\left(\mathbf{y}_{i.} - \mathbf{H}_{i.,-h}\widehat{\boldsymbol{\beta}}_{IPC,i}\right)'\right]\widehat{\mathbf{F}} = \widehat{\mathbf{F}}\widehat{\mathbf{V}}_{nT}, \tag{3.11}$$

where $\mathbf{M}_{G_2} = \mathbf{I}_{T-h} - \mathbf{G}_2(\mathbf{G}_2'\mathbf{G}_2)^{-}\mathbf{G}_2'$, $\mathbf{G}_2 = (\mathbf{e}_{T-h}, \widehat{\mathbf{F}})$, $\widehat{\mathbf{V}}_{nT}$ is a diagonal matrix containing the m largest eigenvalues of the matrix in the brackets on the left hand side of the equation and $\widehat{\mathbf{F}}$ is the matrix of corresponding eigenvectors. The rows of these eigenvectors serve as estimates of the common factors $\mathbf{f}_t'$. To obtain the final estimator of the slope parameters, one can iterate between these two equations until numerical convergence.

The homogeneous counterpart of the estimator (3.9) is

$$\widehat{\boldsymbol{\beta}}_{CCEP} = \left(\sum_{i=1}^{n}\mathbf{H}'_{i.,-h}\mathbf{M}_{G_1}\mathbf{H}_{i.,-h}\right)^{-1}\sum_{i=1}^{n}\mathbf{H}'_{i.,-h}\mathbf{M}_{G_1}\mathbf{y}_{i.}. \tag{3.12}$$

The pooled estimator of Bai (2009) is obtained from the homogeneous versions of the equation system of Song (2013) as

$$\widehat{\boldsymbol{\beta}}_{IPCP} = \left(\sum_{i=1}^{n}\mathbf{H}'_{i.,-h}\mathbf{M}_{G_3}\mathbf{H}_{i.,-h}\right)^{-1}\sum_{i=1}^{n}\mathbf{H}'_{i.,-h}\mathbf{M}_{G_3}\mathbf{y}_{i.}, \tag{3.13}$$

$$\left[\frac{1}{nT}\sum_{i=1}^{n}\left(\mathbf{y}_{i.} - \mathbf{H}_{i.,-h}\widehat{\boldsymbol{\beta}}_{IPCP}\right)\left(\mathbf{y}_{i.} - \mathbf{H}_{i.,-h}\widehat{\boldsymbol{\beta}}_{IPCP}\right)'\right]\widetilde{\mathbf{F}} = \widetilde{\mathbf{F}}\widetilde{\mathbf{V}}_{nT}, \tag{3.14}$$

where $\mathbf{M}_{G_3} = \mathbf{I}_{T-h} - \mathbf{G}_3(\mathbf{G}_3'\mathbf{G}_3)^{-}\mathbf{G}_3'$, $\mathbf{G}_3 = (\mathbf{e}_{T-h}, \widetilde{\mathbf{F}})$, $\widetilde{\mathbf{V}}_{nT}$ is a diagonal matrix containing the m largest eigenvalues of the matrix in the brackets and $\widetilde{\mathbf{F}}$ is the matrix of corresponding eigenvectors.

3.3.3 Determining the Number of Factors and the Lag Length

The number of common factors are determined using the information criterion IC_{p_1} proposed by Bai and Ng (2002). Whenever it is used, following Bai and Ng (2002), we set the maximum numbers of common factors to $m_{max} = \lfloor 8[min(n,T)/100]^{1/4}\rfloor$ where $\lfloor a \rfloor$ denotes the integer part of a. We use this criterion to estimate the number of common factors in the auxiliary variables $\mathbf{w}_{it}$. In addition, the number of common factors in the forecasting equation should be estimated. For the *CCE* and *CCEP* estimators, the parameters of the predictive model are estimated first by these estimators and the number of common factors is chosen using the residuals by IC_{p_1}. For the estimators *IPC* and *IPCP* the strategy is slightly more involved. These estimators require an initial estimate of the parameters of the model to start the iteration of their respective systems of estimation equations. We initialize them by orthogonalizing all variables in the predictive regression model with respect to the common factors of the right hand side variables. The number of common factors in the right hand side variables is determined by IC_{p_1}. After the initial step, we choose the number of common factors in the predictive model by applying the information criterion to the residuals. Given that the initial estimators are consistent, IC_{p_1} chooses the number of common factors consistently.

The lag lengths are determined by minimizing multivariate versions of three information criteria: Akaike information criterion (AIC), Bayesian information criterion (BIC), and Hannan-Quinn (HQ) information criterion. We modified these information criteria for spatially dependent panel data sets. They are computed as

$$\mathrm{AIC}(p,q) = V(p,q) + \frac{2n(p+q+1)}{T}, \tag{3.15}$$

$$\mathrm{BIC}(p,q) = V(p,q) + \frac{n(p+q+1)\log T}{T}, \tag{3.16}$$

$$\mathrm{HQ}(p,q) = V(p,q) + \frac{2n(p+q+1)\log\log T}{T}, \tag{3.17}$$

where $V(p,q) = \log\left[\det\left(\frac{1}{T}\mathbf{R}'_{nT}\mathbf{R}_{nT}\right)\right]$ and $\mathbf{R}_{nT}$ is the $(T \times n)$ matrix of residuals from the predictive model estimated with p, q lags. The maximum number of lags is fixed to 8 which is the maximum forecast horizon considered. In addition to the lag lengths determined by these information criteria, we consider two other possibilities as is done by Marcellino et al. (2006): short lags where all lags are fixed at 2 and long lags where we fix them at 4.

3.4 Empirical Application

3.4.1 Data and Empirical Setup

The dataset comes from the OECD Economic Outlook at quarterly frequency. We have 17 variables, all of which are seasonally adjusted. The sample covers the period between 1990:1 and 2017:4 for 24 OECD countries, hence the final dataset contains 2688 observations. The countries considered are AUS, AUT, BEL, CAN, CHE, DEU, DNK, ESP, FIN, FRA, GBR, GRC, IRL, ISL, ITA, JPN, KOR, LUX, NLD, NOR, NZL, PRT, SWE and USA. Table 3.1 gives the description of each variable in the dataset and their descriptive statistics.

To compare the forecast models and methods we divide the dataset into an estimation and a prediction period. We follow the out-of-sample forecasting methodology of Marcellino et al. (2006). Let us denote the first observation available by T_0 and the last observation by T_2. The estimation period starts in T_0, plus the order of integration of the variable of interest, plus 16 which is the sum of the maximum number of lags that we allow and the maximum forecast horizon that we consider. For all variables we are interested in, this corresponds to 1998:2. The last 16 observations are left out to be predicted. Hence, the initial forecast date, denoted as T_1, is 2013:4. The final forecast date, as a result, the number of forecasts made, depends on the forecast horizon. For instance, for $h = 1$ a total of 16 forecasts are made for each country, for $h = 2$ we have 15 forecasts and so on. We use an expanding forecast scheme such that each prediction uses all past observations to forecast the future values. All variables are standardized to have a variance equal to one for each country before analysis.

Two different accuracy measures are used: the root mean squared error (RMSE) and mean absolute error (MAE). They are computed as

$$\mathrm{RMSE}_i^h = \frac{1}{T_2 - T_1 + 1} \sum_{t=T_1}^{T_2} \varepsilon_{t+h}^2,$$

$$\mathrm{MAE}_i^h = \frac{1}{T_2 - T_1 + 1} \sum_{t=T_1}^{T_2} |\varepsilon_{t+h}|,$$

Table 3.1: Descriptive Statistics

Variable	*Description*	*Transformation*	*Mean*	*Std. Dev.*	*Min*	*Max*
log CPI	Consumer price index	Logarithm	-0.17	0.21	-1.30	0.61
log GDPV	Gross domestic product, volume, market prices	Logarithm	27.84	2.32	23.64	35.11
log PCORE	Core inflation index	Logarithm	-0.16	0.21	-1.31	0.60
log PMGSX	Price of non-commodity imports of goods and services	Logarithm	-0.08	0.19	-1.28	0.54
log PMNW	Price of commodity imports	Logarithm	-0.43	0.52	-1.79	0.67
log PXNW	Price of commodity exports	Logarithm	-0.37	0.45	-1.53	0.69
log TEV	Total expenditure, volume	Logarithm	28.13	2.25	24.24	35.44
log XMKT	Export market for goods and services, volume, USD, 2010 prices	Logarithm	25.74	1.29	21.66	28.52
MPEN	Import penetration, goods and services	-	0.25	0.10	0.08	0.65
MSHA	Share of value imports of good and services in world imports, USD	-	0.03	0.03	0.00	0.19
ULC	Unit labour cost in total economy	-	0.83	0.18	0.29	1.42
SH_MGS	Imports of goods and services, value	Share in GDP	0.39	0.25	0.07	1.94
SH_SAVG	Government saving (net), value	Share in GDP	0.00	0.04	-0.14	0.21
SH_TOCP	Other current payments, general government, value	Share in GDP	0.05	0.02	0.01	0.11
SH_XGS	Exports of goods and services, value	Share in GDP	0.42	0.31	0.09	2.27
SH_YPGTX	Government total disbursements excluding gross interest payments, value	Share in GDP	0.41	0.08	0.20	0.68
UNR	Unemployment rate	-	0.07	0.04	0.00	0.28

where $\varepsilon_{t+h} = \widehat{y}_{t+h} - y_{t+h}$ is the forecast error computed from each model and method. For all forecast horizons h, we report the summary statistics of relative RMSE and MAE of each model and method, relative to the AR(2) model which uses the direct forecasting method. That is, we calculate

$$\text{Relative RMSE(method)}_i^h = \frac{\text{RMSE(method)}_i^h}{\text{RMSE(AR(2)}^D)_i^h},$$
$$\text{Relative MAE(method)}_i^h = \frac{\text{MAE(method)}_i^h}{\text{MAE(AR(2)}^D)_i^h},$$

where RMSE(AR(2)^D) and MAE(AR(2)^D) denote the RMSE and MAE obtained from the forecasts made by an AR(2) model using the direct forecasting method. We mainly focus on the relative accuracy measures averaged over all countries for each forecast horizon but we also report the median over countries.

We use 2 main inflation measures from the dataset to explore the performance of forecasting methods. These are the consumer price inflation ($\Delta \log$ CPI) and core inflation ($\Delta \log$ PCORE). It is possible to reject the unit root hypothesis for each of these two variables using the CD-robust unit root tests developed by Pesaran (2007).[1] Hence, contrary to Stock and Watson (2002b) we assume that the price index series are I(1) and not I(2).

To evaluate the models with additional variables, namely ARDL(p, q) and FARDL(p, q) models, we use two different sets of predicting variables. In the prediction of both inflation measures, first model contains UNR$_{it}$, and second model contains both UNR$_{it}$ and $\Delta \log \text{XMKT}_{it}$. Unemployment rate is the standard predictor of the rate of inflation and is due to the conventional Phillips curve. A large literature exists on the forecast performance of Phillips curve. Closest to our study is Stock and Watson (1999), as they consider factors extracted from a large number of predictors to improve the Phillips curve forecasts. In addition, we use the export market growth rate which is found to be one of the best predictors of inflation.

[1]For each variable x_{it}, the unit root test statistics are computed as $\overline{CIPS} = n^{-1}\sum_{i=1}^{n} t_i(n,T)$ where $t_i(n,T)$ is the t-statistic of the coefficient b_i in the regression $\Delta x_{it} = a_i + b_i x_{i,t-1} + c_i \bar{x}_{t-1} + \sum_{j=0}^{p_i} d_{ij}\Delta \bar{x}_{t-j} + \sum_{j=1}^{p_i} \delta_{ij}\Delta x_{i,t-j}$ with $\bar{x}_t = n^{-1}\sum_{i=1}^{n} x_{it}$. The lag lengths p_i are selected using Akaike information criterion for each country. The test statistics for $\Delta \log$ CPI and $\Delta \log$ PCORE are -3.54 and -3.18, respectively. The 1% critical value for the test equals -2.36 which implies a strong evidence against the unit root hypothesis for each variable.

3.4.1.1 Testing for Cross-Sectional Dependence

Before proceeding with the estimation of the regression models and calculating the accuracy of predictions based on them, we explore the cross-sectional dependence properties of the variables. In Table 3.2, CD test results are reported. Three different CD tests are applied to each original variable and their defactored versions. The first one is the LM test of Breusch and Pagan (1980). This is a general cross-correlation test where the null hypothesis states that the correlation coefficients between all pairs of units in a data set are jointly zero. Under the null hypothesis, the test statistic follows a χ^2 distribution with $n(n-1)/2$ degrees of freedom as T goes to infinity for fixed n. The results show that for each variable in the dataset there is strong evidence against no CD hypothesis.

The disadvantage of the Breusch and Pagan (1980) test is that as n gets larger its variance increases, hence it is not appropriate for panels of large cross-sectional dimension. Thus, we also report the results from a modified version of this test, the Modified BP Test which is distributed as a standard normal for large T and n (see Pesaran, 2015a, for details). Although asymptotically valid, this test suffers from small sample bias, as pointed out by Pesaran et al. (2008). Hence, we also report the results of Frees (1995) tests. The results are in line with the previous test such that the null of no CD can be rejected for any variable in any conventional significance level.

These two tests are general CD tests which cannot detect the types of CD in the data. To see if the results change after removing the unobserved common factors we apply the same tests to defactored variables. We remove unobserved common factors using PC methods where the number of common factors are chosen by the information criterion IC_{p_1} proposed by Bai and Ng (2002). With a few exceptions the test statistics are weaker but still the no CD hypothesis can be rejected for any variable. It should be noted that the properties of such testing procedure is still not very well known in the literature. Juodis and Reese (2018) show that the pre-removal of unobserved common factors by means of subtracting cross-sectional averages may cause an incidental parameters problem in testing for CD. As a result, the CD test proposed by Pesaran (2015b) no longer has the standard normal asymptotic distribution. However, Sarafidis et al. (2009) found that all tests that we use are valid both for original variables and their defactored versions.

Table 3.2: Cross-Sectional Dependence Test Results

	Original Data			Defactored Data		
Variable	*Breusch-Pagan Test*	*Modified BP Test*	*Frees' Test*	*Breusch-Pagan Test*	*Modified BP Test*	*Frees' Test*
$\Delta \log$ CPI	6381.94	259.89	118.98	745.11	19.97	9.10
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta \log$ GDPV	3574.04	140.37	64.24	591.93	13.45	6.11
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta \log$ PCORE	5014.28	201.67	92.32	667.32	16.66	7.58
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta \log$ PMGSX	4127.99	163.95	75.04	654.97	16.13	7.34
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta \log$ PMNW	23109.79	971.87	445.07	1905.42	69.35	31.71
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta \log$ PXNW	16322.64	682.99	312.76	1998.72	73.32	33.53
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta \log$ TEV	4555.43	182.14	83.37	640.28	15.50	7.05
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta \log$ XMKT	22981.69	966.42	442.57	1977.71	72.43	33.12
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MPEN	24811.26	1044.29	478.24	2010.87	73.84	33.77
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MSHA	13647.13	569.11	260.61	2602.43	99.02	45.30
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ULC	25669.71	1080.83	494.97	2782.19	106.67	48.81
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SH_MGS	17208.99	720.72	330.04	2091.44	77.27	35.34
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SH_SAVG	7913.76	325.08	148.84	2387.86	89.89	41.12
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SH_TOCP	10915.93	452.87	207.37	2059.49	75.91	34.72
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SH_XGS	14938.59	624.08	285.78	3137.67	121.80	55.74
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SH_YPGTX	6841.42	279.44	127.94	2068.92	76.31	34.90
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
UNR	5989.45	243.18	111.33	3750.39	147.88	67.68
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: For each variable x_{it}, the Breusch-Pagan Test statistics are computed as $CD_{BP} = T\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\widehat{\kappa}_{ij}^2$ where $\widehat{\kappa}_{ij}$ is the correlation coefficient between x_{it} and x_{jt}. Under the null of no CD, the asymptotic distribution of the test statistic is χ_q^2 with $q = n(n-1)/2$. The Modified BP Test statistics are computed as $CD_M = [n(n-1)]^{-1/2}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}(T\widehat{\kappa}_{ij}^2 - 1)$ which is distributed as $N(0,1)$ under the null of no CD. Frees' Test statistics are computed as $CD_F = V_Q^{-1/2}\left[\frac{2}{n-1}\frac{CD_{BP}}{T} - n(T-1)^{-1}\right]$ which is also distributed as $N(0,1)$ under the null of no CD. p-values are in parentheses. The test statistics given in *Panel b* are computed after removing country fixed effects and the unobserved common factors estimated using PC methods. For each variable the number of common factors are chosen using the information criterion IC_{p_1} of Bai and Ng (2002).

Table 3.3: Distance Based Spatial Dependence Tests for Inflation Variables

Variable	$\Delta \log$ CPI	$\Delta \log$ PCORE	$\Delta \log$ PMGSX	$\Delta \log$ PMNW	$\Delta \log$ PXNW
$\hat{\rho}$	0.74	0.71	0.65	0.92	0.85
t-statistic	51.42	45.55	246.63	172.69	96.71
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: For each demeaned variable x_{it}, the spatial autoregressive coefficient is estimated by maximum likelihood in the regression $\mathbf{x}_{.t} = \rho \mathbf{W}_n \mathbf{x}_{.t} + \varepsilon_{.t}$ where $\mathbf{x}_{.t}$ is the vector of observations of countries stacked for each t and $\mathbf{W}_n$ is the row normalized inverse distance matrix. p-values are in parentheses.

To see if there is evidence for spatial interactions based on geographic distance, we estimate a first order SAR model for each variable by maximum likelihood. We use a row normalized inverse distance matrix as spatial weights. The data on geographical distance come from CEPII GeoDist dataset (Mayer and Zignago, 2011). The results for the inflation variables are given in Table 3.3 whereas the results for other variables are reported in Table 3.4. For consumer price inflation, the SAR coefficient is estimated as 0.74 and it is highly significant. The corresponding estimate for the core inflation is 0.71, also statistically significant. The highest coefficient estimates belong to $\Delta \log$ PMNW and $\Delta \log$ XMKT which are equal to 0.92. As they are foreign trade variables this is an expected result. All remaining variables also have statistically significant SAR coefficients.

The above analysis shows very strong evidence in favor of different types of CD in the variables in our dataset. Hence, it is important to take into account the CD properties in the estimation and forecasting.

3.4.1.2 Global Common Movements in Inflation Series

In this subsection we check the main characteristics of the estimated common components in inflation series. We assume that each inflation variable has a common factor representation given by

$$y_{it} = \boldsymbol{\lambda}_i' \mathbf{g}_t + \varepsilon_{it}, \tag{3.18}$$

where y_{it} is either the consumer price inflation or core inflation standardized and demeaned for each country, $\mathbf{g}_t$ is a vector of common factors with loadings $\boldsymbol{\lambda}_i$, ε_{it} is a scalar error term.

Figure 3.1 plots the estimated common factors in both inflation series. The number of common factors are selected using the IC_{p_1} and they are equal to 2 for consumer price inflation and 1 for core inflation. Throughout the chapter we use principal components (PC) estimates of the common factors, however, this method requires a large number of cross-sections and its finite sample performance can be inferior to that of the maximum likelihood. For comparison, we estimate the common factors with maximum likelihood as well which are also given in the figures. The results show that two methods give very similar estimates of the common factors. Especially the estimates of the first common

Table 3.4: Distance Based Spatial Dependence Tests for Other Variables

$\Delta\log$ GDPV	$\Delta\log$ TEV	$\Delta\log$ XMKT	MPEN	MSHA	ULC	SH_MGS	SH_SAVG	SH_TOCP	SH_XGS	SH_YPGTX	UNR
0.66	0.69	0.92	0.91	0.63	0.86	0.82	0.73	0.69	0.80	0.69	0.65
250.68	261.17	172.15	168.02	234.55	110.01	81.27	48.55	265.17	73.43	261.79	245.84
(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: For each demeaned variable x_{it}, the spatial autoregressive coefficient is estimated by maximum likelihood in the regression $\mathbf{x}_{.t} = \rho \mathbf{W}_n \mathbf{x}_{.t} + \varepsilon_{.t}$ where $\mathbf{x}_{.t}$ is the vector of observations of countries stacked for each t and $\mathbf{W}_n$ is the row normalized inverse distance matrix. p-values are in parentheses.

factor are very higly correlated between the two methods. The principal components and maximum likelihood estimates of the second common factor in consumer price inflation have a slightly lower correlation coefficient but it is still very high, equal to 0.93. Hence, we focus on PC estimates and report the factor loadings estimates by this method.

The estimates of the factor loadings are reported in Table 3.5. The two first common factors in the consumer price inflation show an approximately linearly decreasing section until 1999. For all countries the factor loadings estimates are positive for the first factor. Combined with the estimates of the second common factor and its loadings, we can say that until 1999 most of the countries have experienced decreasing rates of consumer price inflation. This is because the slope of the trends in the two common factor estimates look roughly equal and even for the countries with negative loading estimate for the second factor, they are smaller than the loading of the first factor in absolute terms. This means for most of the countries the common component slope downward until 1999.

In the periods following 1999 the common factors in consumer price inflation look stable until the crisis. Whereas, in the crisis period we see a high variation in both factors. As consumer price inflation contains energy and food prices, this high volatility is an expected result. As can be seen in the last plot, the common factor estimate of core inflation does not contain this volatile period even during the crisis.

Although the estimates of common factors and their loadings show the global tendencies in the inflation measures, it does not show the relative importance of these common components relative to the country specific movements. According to the globalization hypothesis the global drivers of the inflation become more important in the determination of domestic inflation rates over time (Calza, 2009; Ihrig et al., 2010; Bianchi and Civelli, 2015). To check the changing nature of the explanatory power of common components in the inflation series, we compute

$$R_t^2 = \frac{\sum\limits_{i=1}^{n} \sum\limits_{t-4}^{t+4} \left(\widehat{\boldsymbol{\lambda}}_i{}' \widehat{\mathbf{g}}_t \right)^2}{\sum\limits_{i=1}^{n} \sum\limits_{t-4}^{t+4} y_{it}^2}, \tag{3.19}$$

which is an R^2 type statistic calculated for each period in the sample using cross-sectional variation. We used a moving window in the computation to smooth out the sharp increases

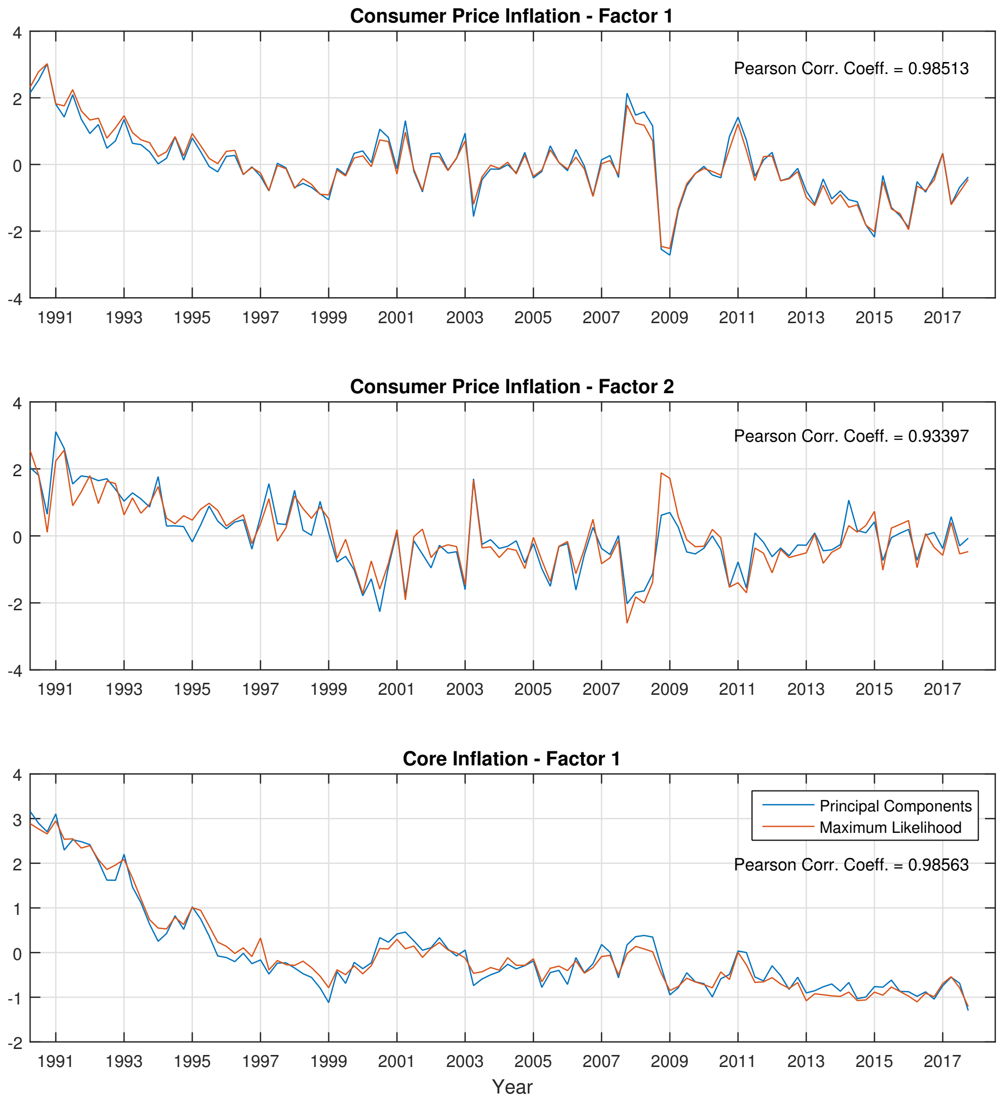


Figure 3.1: Common Factors in Inflation Series

Table 3.5: Factor Loadings of Inflation Series

Country	Consumer Price Inflation		Core Inflation
	λ_{1i}	λ_{2i}	λ_{1i}
AUS	0.47	-0.43	0.40
AUT	0.77	-0.01	0.69
BEL	0.74	-0.35	0.63
CAN	0.63	-0.17	0.40
CHE	0.84	0.25	0.89
DEU	0.77	0.04	0.66
DNK	0.64	-0.37	0.50
ESP	0.86	0.05	0.86
FIN	0.73	-0.11	0.62
FRA	0.86	-0.18	0.78
GBR	0.73	0.29	0.60
GRC	0.73	0.53	0.88
IRL	0.61	-0.30	0.36
ISL	0.25	-0.21	0.23
ITA	0.83	0.30	0.86
JPN	0.33	0.37	0.48
KOR	0.58	0.40	0.78
LUX	0.77	-0.28	0.64
NLD	0.60	-0.05	0.49
NOR	0.33	-0.21	0.39
NZL	0.55	-0.40	0.28
PRT	0.78	0.43	0.91
SWE	0.74	0.21	0.67
USA	0.75	-0.22	0.74

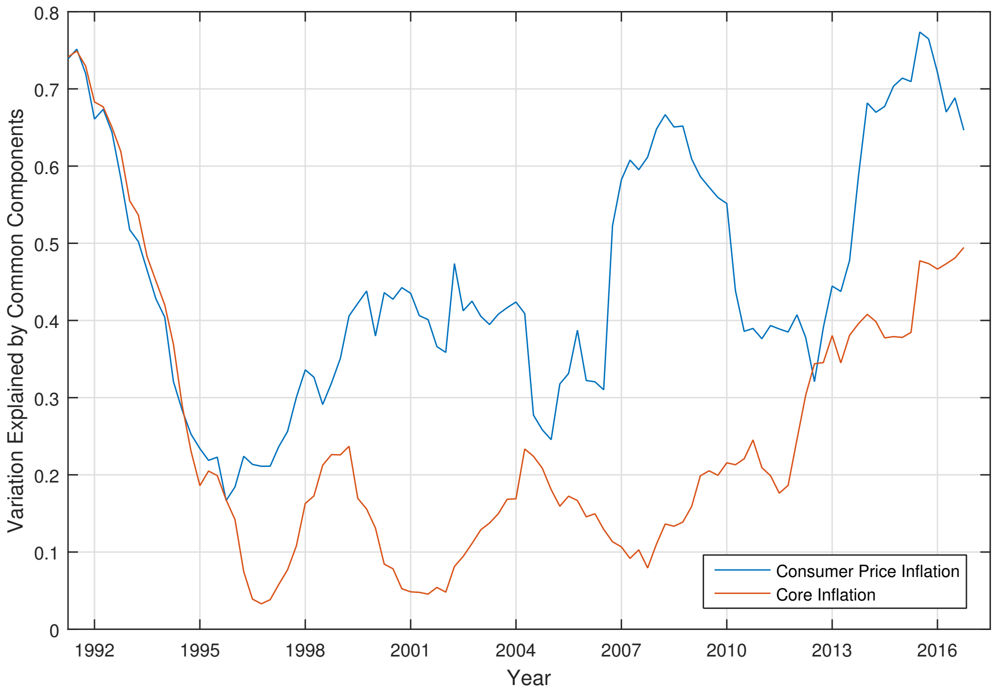


Figure 3.2: Explanatory Power of Common Factors

and decreases.

This statistic is plotted in Figure 3.2. As can be seen, there is a very high heterogeneity in the explanatory power of the common factors over time. This is especially true for the consumer price inflation. From the beginning of the sample to around 1996 the ratio of the variation in common components relative to the total variation decreases. Afterwards, an increase is observed. For consumer price inflation the peak in the crisis period is worth mentioning. Although this is not a formal test of the globalization hypothesis, we can say that our data set shows evidence in support of it, especially after mid-1990's.

3.4.2 Results

In this section out-of-sample forecasting results are discussed. To save space, the results are reported only for horizons $h = 2$, $h = 4$ and $h = 8$. In what follows the focus is on the results with the mean relative RMSE and mean relative MAE averaged over two inflation measures, consumer price inflation and core inflation. These results are reported in Tables 3.6-3.9. Additional results, namely the results on mean and median relative RMSE, mean and median relative MAE for individual inflation series are given in Appendix C. This breakdown into two different inflation measures is important because of the differences in the importance of common global movements in them. Hence, we comment on these results separately as well.

3.4.2.1 Inflation Forecasts: Main Results

The mean relative RMSE results for inflation forecasts using the direct method are given in Table 3.6. In the case of AR(p) models and when $h = 2$, the best performing strategy is found to be a short lag combined with the GLS estimator. However, the difference between this method and the benchmark is practically invisible as the relative RMSE equals 1. When $h = 4$, the superiority of GLS estimator is more pronounced, such that the mean relative RMSE is 0.97 when it is combined with a long lag. When longest horizon $h = 8$ is considered, the conclusion does not change such that GLS estimator combined with a long lag has a mean relative RMSE equal to 0.97.

Using additional indicators improves the forecast performance slightly, especially in long horizons. In the case of an ARDL(p, q) model with a smaller set of additional indicators, that is the Phillips curve, MG estimator gives the best results when it is combined with long lags. In this case, it reaches the lowest mean relative RMSE which is equal to 0.95.

Augmenting the predictive equations with common factors improves the forecasts in the case of the AVA method. For FAR(p) models and when $h = 2$, the lowest mean relative RMSE is reached with the estimator CCE combined with a short lag and the AVA. This strategy gives a relative RMSE equal to 0.95. Without common factors the lowest mean relative RMSE was 0.98 which shows a 3% improvement from using global common factors. For $h = 4$ and $h = 8$, the best performing forecast strategy is still the same. In this case there is a larger improvement from the usage of global common factors such that the gain relative to the benchmark is 8%. To summarize the CCE estimator combined with the AVA method and a fixed and short lag length gives the best forecast results.

Combining global common factors with a well specified model with additional indicators provides the best forecast performance. FARDL(p, q) model with 1 additional indicator, namely the unemployment rate, combined with the AVA and short lag gives an average relative RMSE equal to 0.95 for $h = 2$ when estimated with $IPCP$. For $h = 4$ and $h = 8$, same model estimated with IPC is a successful strategy too, such that the average relative RMSE equals 0.92 and 0.91 in these cases, respectively. However, among all FARDL(p, q) models, best forecasts are made by the model with a larger set of indicators, combined with AVA when estimated with IPC for short horizons. Overall, the FARDL(p, q) model provides up to 9% improvement over the benchmark model.

To summarize, according to the average relative RMSE, best forecasts of consumer price inflation is made using global common factors. The models using observed variables and estimated factors by means of the the AVA are the best performers when estimated using the individual estimator CCE or pooled estimator $IPCP$. Furthermore, in simpler models without observed variables heterogeneous estimators perform better, whereas for more complex models pooling looks more advantageous.

The corresponding results for the iterated method are given in Table 3.7. The conclusions made above from the comparison of heterogeneous and homogeneous estimators, and the RBA and AVA approaches are broadly confirmed in the case of iterated forecasts. First of all, the comparison of the direct and iterated methods shows mixed results. The AR(p) model with short lags gives a average relative RMSE equal to 1.01 when it is estimated by the OLS for $h = 2$. For $h = 4$ and $h = 8$, this value equals 0.99 and 1.00, respectively. Hence, we cannot conclude on the optimal method in this case.

This changes for other models. For the ARDL(p, q) model estimated with a larger set of variables and the FE, the average relative RMSE equals 0.97, 0.94 and 0.95 for $h = 2$, $h = 4$ and $h = 8$, respectively, when lags are chosen by the BIC. This shows an improvement over the direct method for which the smallest relative RMSE was found to be 0.98.

For the factor augmented models, direct method provides worse forecasts than the iterated method for most of the cases. In the case of the iterated method, FAR(p) model improves slightly over the same model with the direct method. For all horizons, FAR(p) model combined with the AVA is the best performer when estimated with IPC. The improvement over the benchmark model without common factors reaches up to 10% for the middle horizon. This means a 2% improvement over the direct method. For other models, the direct method performs better but overall the optimal prediction method is FAR(p) model combined with the AVA, estimated with IPC.

The mean relative MAE results using the direct method are given in Table 3.8 and the corresponding results for the iterated method are reported in Table 3.9. The conclusions from the mean relative MAE are similar to the conclusions reached using the mean relative RMSE. However, in terms of bias the advantage of using common factors is more pronounced.

Once more, the differences between the direct and iterated methods are not very big in the case of AR(p) models. For the ARDL(p, q) models however, some important differences exist. For instance, for $h = 4$ the lowest mean relative MAE is reached by the iterated method which is equal to 0.93. This is for the ARDL(p, q) model with a large set of observables estimated by FE and when the lag lengths are chosen by BIC. The lowest value for the direct method is 0.98 which means that iterated method improves the predictions by a factor of 5%.

The models with common factors estimated by means of the AVA perform better in terms of bias too and the gains are even bigger in this case. For instance, $h = 4$ the FAR(p) model combined with the AVA and the iterated method is the best performer when estimated with IPC. The gain in bias over the benchmark is 12%. The corresponding number for the direct method is 10%. For the models with observed variables, the direct method is more advantageous in terms of bias. Once more, for these models pooling provide benefits over heterogeneous estimates.

3.4.2.2 Consumer Price Inflation

Tables C1-C8 report the results specific to consumer price inflation. The first one, Table C1 gives the results on the mean relative RMSE for the direct prediction method whereas Table C2 contains the corresponding results for the iterated method. First, let us focus on the optimal forecasts with the simple AR(p) models. The results show that having shorter lags in the autoregressive model improves the forecasts. For $h = 2$, the best forecasts are made by the GLS with a short lag and the direct method, however its average relative RMSE is only 0.99. For $h = 4$, OLS is the best performer with the iterated method and short lags. It improves 5% over the benchmark. In the longest horizon, once more GLS combined with the direct method and long lags is the best choice.

Using additional indicators improves the forecasts. ARDL(p, q) model with a larger set of additional predictors provide better forecasts with the iterated method. This shows that the export market growth rate has marginal ability to predict consumer price inflation in Phillips curve forecasts. For $h = 2$, the best forecast is done by the FE. The choice of lag determination method looks unimportant, such that all information criteria give the same mean relative RMSE. Same methodology is the optimal choice for other horizons as well. For $h = 4$, the improvement in mean relative RMSE goes up to 8%.

Augmenting the predictive equations with common factors improves the forecasts more in the case of consumer price inflation, and moreover, this time the conclusion on the superiority of the FAR(p) model over the AR(p) model is much more pronounced. For instance, with the RBA, the lowest relative RMSE is equal to 1.07 for $h = 2$ but with the AVA, the gain in precision goes up to 8% in this horizon. The minimum value is achieved with IPC combined with a short lag and the iterative method. For other horizons the results are similar. In the case of $h = 4$, the forecasts with the the AVA, IPC and the iterative method reaches an average RMSE of 0.84. This means that the gain in precision has doubled over the models with observed variables.

Best forecasts are made by the FAR(p) model estimated with the IPC when it is combined with the AVA, short lags and the iterated method. However, FARDL(p, q) also improves the forecasts considerably. The conclusions on the relationship between the model complexity and the comparison between the performance of the heterogeneous and homogeneous estimators are visible in the case of consumer price inflation too. For instance, for $h = 2$ the best forecasts are made by the FARDL(p, q) model with short lags when it is estimated with the $IPCP$.

To summarize, the iterated method performs better than the direct method in all horizons, the AVA dominates RBA without exceptions, and homogeneous estimation of more complex models is better whereas the simpler models provide better forecasts with heterogeneous estimators.

These conclusions are confirmed when we consider the relative MAE. Moreover, in terms of bias the difference between the benchmark model and the factor augmented regressions is bigger. For instance, for $h = 2$, the gain from using common factors by means of the AVA goes up to 17% with the FAR(p) model estimated with the IPC.

The results on using the median over the countries instead of the mean show that the conclusions are not driven by a few exceptional countries. In fact this is most of the time the contrary such that the difference from the benchmark is larger from using observables and common factors. Only the comparison between the FAR(p) model and the FARDL(p, q) model changes. For instance, as can be seen in Tables C5 and C6, the best prediction is done by the smaller FARDL(p, q) model estimated with the $IPCP$ and long lags. In this case the gain over the benchmark is 19%.

3.4.2.3 Core Inflation

The results specific to core inflation are reported in Tables C9-C16. For the forecasts using the direct scheme the results are reported in Table C9 and the corresponding results for the iterated method are given in Table C10. The conclusions on the AR(p) model are similar to the results of the previous variable. For this variable, long lags with the direct method are the best choice. For all horizons, GLS estimator has the lowest average RMSE. In this case, iterated method does worse than the benchmark in all cases.

Using observed variables improve the forecasts only by 2% for $h = 2$ for both direct and iterated methods. However for longer horizons, the larger ARDL(p, q) model estimated with FE provides up to 5% improvement over the benchmark with iterated method when the lag lengths are chosen with BIC.

Once more, augmenting the AR(p) model with common factors provides large gains in precision in the case of the AVA. However, these gains are limited in comparison with the case of consumer price inflation. For instance, for $h = 8$, the best relative RMSE of the FAR(p) model equals 0.90 with the AVA and direct method whereas the minimum value is 0.92 for the AVA and the iterated method. In both cases best predictions are made by the $IPCP$ combined with short lags.

Finally, the most general model, FARDL(p, q), provides the optimal forecasting scheme when it is combined with the AVA and the direct method. For $h = 2$, the best forecast is made when the model has the large set of observables, short lags and estimated with $IPCP$. The average relative RMSE equals 0.96 in this case. For this case, RBA does as good as the AVA. In the case of $h = 8$, IPC is still the best performer. In this case gains from using observables and common factors go up to 12%. Overall, the large FARDL(p, q) model is the best performer in terms of average RMSE. When it is combined with the AVA approach and the direct method it provides the best forecasts.

We can confirm these results with the help of MAE. These results are given in Tables C11 and C12 for the direct and the iterated methods, respectively. Namely, the FARDL(p, q) models provide the best predictions when they are combined with the AVA, the $IPCP$ estimator and the direct forecasting method.

If we focus on the median over the countries instead of the mean, once more we see that the conclusions are robust. As can be seen in Tables C13 and C14, as in the case of consumer price inflation, the best prediction is done by the smaller FARDL(p, q) model estimated with the $IPCP$ and short lags regardless of the prediction method. Thee gain over the benchmark is 19%.

3.5 Conclusion

In this chapter, we empirically evaluated different strategies of forecasts using panel data. The iterated and direct forecasts are compared using a dataset containing seventeen quarterly macroeconomic variables from 24 OECD countries. We reported forecast accuracy measures based on out-of-sample forecasts for two different inflation measures. The results showed that (i) only for the models without common factors iterated forecasting scheme is superior to the direct scheme according to all measures of forecast accuracy; (ii) however, lag length selection is much more important in the case of iterative method; misspecification of the model can lead to worse forecasts; (iii) the models with global common factors estimated using principal components methods from the observations on all countries in the sample improves the forecast accuracy considerably; (iv) using indicators in addition to lags of the variables of interest and common factors improves the forecast performance

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Table 3.6: Mean Relative RMSE for Direct Prediction Method

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.01	1.02	1.04	1.04	1.03	1.03	1.02	1.04	1.03	1.03	1.03	1.04	1.01	1.01	1.06	1.08	1.00	**1.00**	1.05	1.06
			4	0.99	0.99	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	0.99	**0.97**	1.04	1.05	1.00	1.00	1.08	1.07
			8	1.00	1.00	1.05	1.05	1.00	1.01	1.05	1.04	1.00	1.01	1.05	1.05	0.99	**0.97**	1.04	1.04	1.00	0.99	1.06	1.04
ARDL	$\mathbf{x}_{1,it}$		2	1.01	1.01	1.01	1.03	1.02	1.01	**0.99**	1.04	1.02	1.01	1.00	1.03	1.06	1.03	1.06	1.07	1.03	1.01	1.04	1.04
			4	1.02	**1.00**	1.00	1.03	1.02	1.01	1.00	1.04	1.02	1.01	1.01	1.03	1.08	1.01	1.04	1.04	1.06	1.01	1.06	1.03
			8	1.06	1.01	1.01	0.97	1.04	1.00	1.02	0.97	1.04	1.00	1.01	0.97	1.10	1.01	1.01	**0.95**	1.06	1.00	1.03	0.96
ARDL	$\mathbf{x}_{2,it}$		2	1.01	1.01	0.99	1.05	1.02	1.01	0.98	1.05	1.02	1.01	**0.98**	1.05	1.05	1.01	1.03	1.07	1.02	1.00	1.02	1.05
			4	1.01	**0.98**	0.99	1.04	1.03	1.01	0.99	1.05	1.03	1.01	0.99	1.04	1.10	1.01	1.02	1.05	1.05	1.00	1.04	1.03
			8	1.06	1.00	1.01	1.00	1.06	1.00	1.02	0.98	1.06	1.00	1.01	0.99	1.14	1.05	1.04	0.99	1.08	1.02	1.05	**0.98**
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.08	1.04	1.06	1.03	1.08	1.07	1.06	**1.03**	1.08	1.06	1.06	1.03	1.08	1.03	1.09	1.09	1.06	1.05	1.10	1.10
			4	1.10	1.08	1.07	1.06	1.11	1.09	1.07	1.07	1.11	1.09	1.07	1.06	**1.05**	1.05	1.08	1.08	1.07	1.06	1.11	1.11
			8	1.08	1.05	1.11	1.08	1.08	1.06	1.13	1.11	1.08	1.06	1.12	1.10	1.08	1.06	1.10	1.10	1.07	**1.05**	1.11	1.10
FAR		*AVA*	2	1.04	1.02	1.00	0.99	1.04	1.03	1.00	0.99	1.04	1.03	1.00	0.99	0.99	0.98	0.98	0.98	**0.95**	0.95	0.96	0.96
			4	1.05	0.98	1.00	0.98	1.06	1.03	1.00	0.99	1.06	1.03	1.00	0.99	0.94	0.95	0.94	0.95	**0.92**	0.93	0.92	0.92
			8	1.02	0.99	1.05	1.00	1.02	1.00	1.07	1.05	1.02	1.00	1.06	1.01	0.96	1.00	0.95	0.96	**0.92**	0.95	0.94	0.93
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.11	1.10	1.04	**1.03**	1.11	1.10	1.04	1.06	1.11	1.10	1.04	1.06	1.09	1.13	1.12	1.08	1.09	1.11	1.10	1.09
			4	1.07	1.10	1.06	1.03	1.07	1.07	1.06	1.03	1.07	1.07	1.06	**1.03**	1.06	1.16	1.08	1.06	1.06	1.08	1.09	1.07
			8	1.04	1.15	1.05	**1.01**	1.04	1.16	1.06	1.02	1.04	1.16	1.05	1.02	1.11	1.22	1.09	1.07	1.03	1.05	1.06	1.04
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.05	3.05	0.99	0.96	1.05	3.22	0.99	0.96	1.05	3.17	0.99	0.96	1.04	4.07	1.02	1.00	0.97	3.73	0.96	**0.95**
			4	1.07	3.56	0.99	0.95	1.07	3.72	0.99	0.96	1.07	3.69	0.99	0.95	1.05	4.92	0.99	0.98	0.98	4.24	0.92	**0.92**
			8	1.07	2.66	1.03	0.99	1.07	2.77	1.03	1.00	1.07	2.70	1.03	1.00	1.07	4.14	0.95	0.96	1.00	3.53	0.92	**0.91**
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.14	1.10	1.05	1.04	1.14	1.11	1.05	1.04	1.14	1.11	1.05	**1.04**	1.25	1.19	1.09	1.06	1.15	1.18	1.10	1.07
			4	1.10	1.05	1.01	**0.99**	1.10	1.04	1.02	1.00	1.10	1.04	1.01	1.00	1.32	1.36	1.10	1.01	1.12	1.15	1.07	1.04
			8	1.06	1.04	1.06	**1.00**	1.06	1.01	1.06	1.02	1.06	1.01	1.05	1.01	1.27	1.43	1.07	1.04	1.09	1.07	1.06	1.02
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.09	2.77	1.00	0.97	1.09	3.13	1.00	0.96	1.09	2.85	1.00	0.96	1.30	3.90	1.03	1.00	1.03	3.57	0.96	**0.94**
			4	1.08	3.67	0.96	0.93	1.08	3.94	0.97	0.93	1.08	3.90	0.96	0.93	1.32	4.12	0.97	0.95	1.01	3.79	0.95	**0.91**
			8	1.07	2.74	1.02	0.97	1.07	2.77	1.03	0.99	1.07	2.75	1.02	0.98	1.27	4.19	0.95	0.97	1.06	2.98	0.92	**0.92**

Notes: The results show the mean relative RMSE of each model and estimator made by direct method, relative to the RMSE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. "Long Lag" stands for $p = 4$, $q = 4$, whereas "Short Lag" stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \mathrm{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\mathrm{UNR}_{it}, \Delta \log \mathrm{XMKT}_{it})'$.

Table 3.7: Mean Relative RMSE for Iterated Prediction Method

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.03	1.03	1.04	1.06	1.07	1.08	1.03	1.04	1.03	1.03	1.04	1.06	1.03	1.03	1.09	1.12	**1.01**	1.02	1.08	1.09
			4	1.01	1.02	1.04	1.05	1.06	1.07	1.03	1.03	1.01	1.02	1.04	1.04	1.02	1.02	1.11	1.14	**0.99**	1.01	1.08	1.09
			8	1.01	1.02	1.05	1.05	1.05	1.06	1.02	1.03	1.01	1.02	1.05	1.03	1.01	1.01	1.06	1.06	**1.00**	1.02	1.07	1.06
ARDL	$\mathbf{x}_{1,it}$		2	1.02	1.02	1.01	1.08	1.04	1.04	**1.00**	1.05	1.02	1.04	1.01	1.07	1.06	1.04	1.07	1.11	1.03	1.02	1.06	1.07
			4	0.99	0.99	0.99	1.10	1.01	1.01	**0.99**	1.05	1.00	1.01	0.99	1.09	1.05	1.03	1.07	1.12	1.01	1.00	1.04	1.07
			8	1.00	1.01	0.99	1.12	1.02	1.02	**0.97**	1.06	1.01	1.02	0.98	1.09	1.06	1.04	1.03	1.09	1.03	1.02	1.02	1.07
ARDL	$\mathbf{x}_{2,it}$		2	1.01	1.01	0.97	1.08	1.04	1.04	**0.97**	1.08	1.01	1.03	0.97	1.08	1.02	1.00	1.03	1.10	1.02	1.00	1.04	1.09
			4	1.00	0.98	0.95	1.11	1.02	1.01	**0.94**	1.11	1.00	1.01	0.95	1.10	1.01	0.98	1.01	1.12	0.99	0.98	1.01	1.10
			8	1.00	0.99	0.97	1.16	1.03	1.02	**0.95**	1.13	1.00	1.01	0.97	1.15	1.02	1.01	1.01	1.12	1.01	1.00	1.01	1.11
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.11	1.07	1.08	1.05	1.14	1.13	1.08	**1.05**	1.11	1.10	1.08	1.05	1.08	1.06	1.13	1.11	1.08	1.07	1.14	1.13
			4	1.12	1.07	1.09	1.06	1.15	1.14	1.09	**1.05**	1.12	1.11	1.09	1.06	1.09	1.07	1.15	1.13	1.09	1.07	1.16	1.16
			8	1.09	1.06	1.06	1.04	1.12	1.10	1.05	**1.03**	1.09	1.07	1.05	1.04	1.10	1.06	1.07	1.06	1.07	1.07	1.08	1.10
FAR		*AVA*	2	1.06	0.98	1.00	0.99	1.12	1.07	1.00	0.99	1.06	1.02	1.00	0.99	0.98	0.96	0.98	0.99	0.96	**0.94**	0.98	0.98
			4	1.05	0.95	1.00	0.99	1.09	1.04	1.00	0.99	1.05	0.98	1.00	0.99	0.95	0.94	0.94	0.95	0.92	**0.90**	0.94	0.94
			8	1.04	0.95	1.04	1.03	1.06	1.01	1.02	1.02	1.04	0.96	1.03	1.03	1.03	1.07	1.00	1.00	0.95	**0.92**	0.95	0.95
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.12	1.07	1.07	**1.07**	1.12	1.10	1.07	1.08	1.12	1.07	1.07	1.08	1.11	1.11	1.11	1.10	1.10	1.18	1.09	1.08
			4	1.11	1.11	1.05	1.04	1.11	1.11	**1.04**	1.06	1.11	1.10	1.04	1.06	1.10	1.17	1.10	1.09	1.08	1.21	1.09	1.08
			8	1.04	1.02	1.00	**0.99**	1.05	1.01	0.99	0.99	1.05	1.00	1.00	0.99	1.03	1.11	1.02	1.00	1.02	1.18	1.01	1.01
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.08	3.38	0.99	0.97	1.10	4.26	0.99	0.96	1.10	3.71	0.99	0.97	1.04	4.99	1.02	1.00	0.98	3.94	0.98	**0.96**
			4	1.04	4.69	0.98	0.95	1.06	>5	0.97	0.94	1.06	4.79	0.98	0.95	1.00	>5	0.99	0.98	0.95	>5	0.94	**0.93**
			8	1.05	>5	1.01	0.98	1.06	>5	0.99	0.97	1.06	>5	1.01	0.98	1.06	>5	0.98	1.00	0.98	>5	**0.96**	0.96
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.09	1.13	1.09	1.04	1.10	1.10	1.08	**1.04**	1.10	1.12	1.08	1.04	1.27	1.23	1.12	1.05	1.13	1.11	1.11	1.07
			4	1.10	1.13	1.08	1.00	1.10	1.12	1.08	**1.00**	1.10	1.12	1.08	1.00	1.25	1.34	1.10	1.01	1.10	1.08	1.10	1.05
			8	1.01	1.05	1.04	0.98	1.02	1.05	1.03	**0.97**	1.02	1.05	1.04	0.98	1.10	1.31	1.03	0.99	1.08	1.05	1.03	1.00
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.10	3.37	1.01	0.96	1.12	3.56	1.01	**0.96**	1.11	3.33	1.01	0.96	1.36	3.98	1.03	0.99	1.04	3.63	0.99	0.97
			4	1.05	>5	0.99	0.95	1.06	>5	0.99	0.94	1.06	>5	0.99	0.95	1.38	>5	0.96	0.94	0.98	4.92	0.94	**0.93**
			8	1.05	>5	1.02	0.98	1.06	>5	1.02	0.97	1.06	>5	1.02	0.98	1.22	>5	0.98	0.99	1.00	>5	0.97	**0.97**

Notes: The results show the mean relative RMSE of each model and estimator made by iterated method, relative to the RMSE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. “Long Lag” stands for $p = 4$, $q = 4$, whereas “Short Lag” stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \mathrm{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\mathrm{UNR}_{it}, \Delta \log \mathrm{XMKT}_{it})'$.

Table 3.8: Mean Relative MAE for Direct Prediction Method

				AIC				BIC				HQ				Long Lag				Short Lag			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.02	1.03	1.04	1.05	1.03	1.03	1.03	1.06	1.03	1.03	1.04	1.05	1.01	1.01	1.07	1.09	1.00	**1.00**	1.07	1.07
			4	1.00	1.00	1.06	1.07	1.05	1.06	1.07	1.07	1.05	1.06	1.07	1.07	0.98	**0.97**	1.07	1.07	1.00	1.01	1.12	1.11
			8	1.00	1.00	1.08	1.07	1.01	1.02	1.08	1.07	1.01	1.02	1.08	1.08	0.99	**0.97**	1.07	1.06	1.00	0.99	1.09	1.07
ARDL	$\mathbf{x}_{1,it}$		2	1.02	1.01	1.01	1.04	1.02	1.01	**0.99**	1.05	1.02	1.01	1.00	1.04	1.07	1.03	1.07	1.07	1.03	1.01	1.04	1.05
			4	1.03	**1.00**	1.01	1.05	1.03	1.01	1.01	1.06	1.03	1.01	1.02	1.05	1.08	1.01	1.06	1.06	1.07	1.02	1.08	1.04
			8	1.07	1.01	1.03	0.96	1.05	1.01	1.04	0.96	1.05	1.01	1.03	0.96	1.12	1.01	1.03	0.95	1.06	1.00	1.05	**0.95**
ARDL	$\mathbf{x}_{2,it}$		2	1.01	1.00	0.98	1.07	1.01	1.00	0.98	1.07	1.01	1.00	**0.98**	1.07	1.06	1.00	1.02	1.08	1.01	0.99	1.02	1.06
			4	1.01	**0.98**	0.98	1.06	1.03	1.01	0.98	1.07	1.03	1.01	0.98	1.07	1.08	0.99	1.02	1.07	1.05	0.99	1.05	1.04
			8	1.06	1.01	1.03	0.99	1.07	1.01	1.04	0.98	1.07	1.01	1.03	0.99	1.16	1.05	1.06	0.99	1.08	1.02	1.07	**0.97**
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.08	1.04	1.07	1.04	1.08	1.07	1.06	1.03	1.08	1.05	1.07	1.04	1.08	**1.03**	1.09	1.09	1.06	1.05	1.11	1.10
			4	1.11	1.09	1.09	1.07	1.12	1.09	1.09	1.08	1.12	1.09	1.09	1.08	1.04	**1.04**	1.10	1.09	1.08	1.06	1.15	1.14
			8	1.12	1.08	1.16	1.13	1.12	1.08	1.17	1.16	1.12	1.08	1.16	1.14	1.10	1.07	1.15	1.14	1.10	**1.07**	1.16	1.15
FAR		*AVA*	2	1.05	1.02	1.01	1.00	1.05	1.03	1.01	1.00	1.05	1.03	1.01	1.00	0.99	0.98	0.98	0.99	**0.94**	0.94	0.95	0.95
			4	1.08	0.98	1.03	1.01	1.08	1.05	1.03	1.02	1.08	1.05	1.02	1.01	0.93	0.94	0.93	0.94	**0.90**	0.92	0.92	0.92
			8	1.05	0.99	1.09	1.02	1.05	1.01	1.11	1.08	1.05	1.01	1.09	1.03	0.96	0.99	0.94	0.95	**0.91**	0.93	0.93	0.92
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.10	1.10	1.03	**1.01**	1.10	1.09	1.04	1.04	1.10	1.10	1.03	1.04	1.09	1.15	1.11	1.07	1.09	1.12	1.08	1.07
			4	1.07	1.09	1.07	**1.02**	1.07	1.07	1.06	1.02	1.07	1.05	1.07	1.02	1.05	1.16	1.10	1.07	1.05	1.09	1.12	1.07
			8	1.06	1.15	1.09	**1.04**	1.06	1.16	1.09	1.05	1.06	1.16	1.09	1.04	1.14	1.22	1.13	1.10	1.04	1.06	1.10	1.07
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.06	3.29	0.99	0.96	1.06	3.53	0.99	0.96	1.06	3.47	0.99	0.96	1.04	4.55	1.03	1.00	0.96	4.14	0.94	**0.93**
			4	1.09	3.91	1.01	0.95	1.09	4.16	1.00	0.96	1.09	4.12	1.01	0.95	1.06	>5	0.98	0.97	0.97	4.72	0.91	**0.91**
			8	1.09	2.69	1.05	1.00	1.09	2.73	1.06	1.02	1.09	2.71	1.06	1.02	1.06	4.25	0.92	0.94	1.00	3.80	0.90	**0.89**
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.12	1.10	1.05	1.03	1.12	1.09	1.05	1.03	1.12	1.09	1.05	**1.03**	1.25	1.21	1.08	1.03	1.14	1.18	1.09	1.05
			4	1.09	1.06	1.00	**0.98**	1.09	1.05	1.02	0.99	1.09	1.06	1.00	0.98	1.37	1.37	1.11	1.00	1.12	1.14	1.08	1.05
			8	1.08	1.04	1.09	1.02	1.08	**1.01**	1.09	1.04	1.08	**1.01**	1.09	1.03	1.29	1.46	1.10	1.07	1.10	1.07	1.09	1.04
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.09	2.95	1.00	0.96	1.09	3.39	1.01	0.96	1.09	3.03	1.01	0.96	1.33	4.34	1.03	1.00	1.02	4.07	0.95	**0.93**
			4	1.09	4.09	0.96	0.93	1.09	4.54	0.98	0.93	1.09	4.48	0.97	0.93	1.37	4.33	0.96	0.94	1.00	4.20	0.94	**0.90**
			8	1.09	2.89	1.04	0.98	1.09	2.89	1.05	1.00	1.09	2.88	1.04	0.99	1.29	4.53	0.93	0.95	1.07	3.12	0.91	**0.89**

Notes: The results show the mean relative MAE of each model and estimator made by direct method, relative to the MAE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. "Long Lag" stands for $p = 4$, $q = 4$, whereas "Short Lag" stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \text{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\text{UNR}_{it}, \Delta \log \text{XMKT}_{it})'$.

Table 3.9: Mean Relative MAE for Iterated Prediction Method

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.03	1.04	1.04	1.07	1.08	1.09	1.04	1.04	1.03	1.04	1.04	1.06	1.03	1.03	1.10	1.13	**1.02**	1.02	1.10	1.11
			4	1.02	1.04	1.07	1.09	1.09	1.11	1.06	1.06	1.02	1.04	1.07	1.07	1.03	1.03	1.15	1.18	**1.00**	1.02	1.12	1.14
			8	1.02	1.04	1.08	1.09	1.08	1.09	1.05	1.05	1.02	1.04	1.08	1.05	1.03	1.03	1.10	1.09	**1.02**	1.04	1.10	1.09
ARDL	$\mathbf{x}_{1,it}$		2	1.02	1.02	1.01	1.11	1.05	1.04	**1.00**	1.06	1.03	1.04	1.01	1.09	1.07	1.03	1.08	1.12	1.04	1.02	1.07	1.09
			4	0.99	0.99	1.00	1.15	1.03	1.02	**0.99**	1.08	1.00	1.02	1.00	1.13	1.07	1.04	1.10	1.16	1.02	1.00	1.07	1.10
			8	1.00	1.01	1.00	1.16	1.04	1.03	**0.97**	1.07	1.02	1.03	0.99	1.12	1.08	1.05	1.05	1.11	1.04	1.03	1.05	1.09
ARDL	$\mathbf{x}_{2,it}$		2	1.01	1.00	0.96	1.10	1.04	1.03	**0.96**	1.11	1.01	1.03	0.96	1.10	1.02	0.99	1.02	1.12	1.01	0.99	1.03	1.11
			4	0.99	0.98	0.95	1.17	1.03	1.03	**0.93**	1.16	0.99	1.02	0.94	1.16	1.01	0.97	1.02	1.17	0.99	0.97	1.03	1.15
			8	1.01	0.99	0.98	1.20	1.05	1.04	**0.95**	1.18	1.01	1.02	0.97	1.19	1.02	1.01	1.02	1.15	1.00	0.99	1.02	1.14
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.11	1.07	1.09	**1.06**	1.14	1.12	1.09	1.06	1.11	1.10	1.09	1.06	1.08	1.06	1.14	1.12	1.09	1.06	1.16	1.14
			4	1.15	1.08	1.12	1.08	1.19	1.17	1.11	**1.07**	1.15	1.13	1.12	1.07	1.10	1.07	1.19	1.16	1.11	1.09	1.21	1.20
			8	1.11	1.08	1.09	1.06	1.16	1.14	1.07	**1.04**	1.11	1.10	1.08	1.06	1.12	1.08	1.10	1.09	1.10	1.09	1.11	1.14
FAR		*AVA*	2	1.08	0.98	1.02	1.00	1.14	1.07	1.01	1.00	1.08	1.01	1.01	1.00	0.99	0.96	0.99	0.99	0.95	**0.93**	0.97	0.97
			4	1.07	0.95	1.04	1.01	1.14	1.07	1.03	1.01	1.07	0.99	1.03	1.02	0.93	0.92	0.94	0.94	0.90	**0.88**	0.94	0.94
			8	1.07	0.96	1.07	1.06	1.10	1.03	1.05	1.05	1.07	0.97	1.06	1.06	1.02	1.08	0.99	1.00	0.94	**0.90**	0.95	0.94
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.12	1.07	1.06	**1.05**	1.11	1.08	1.06	1.06	1.11	1.07	1.06	1.06	1.11	1.12	1.10	1.08	1.09	1.16	1.09	1.07
			4	1.12	1.09	1.07	**1.05**	1.12	1.11	1.05	1.07	1.12	1.08	1.06	1.07	1.11	1.14	1.13	1.09	1.09	1.19	1.11	1.09
			8	1.05	1.00	1.01	0.99	1.05	1.01	1.00	1.00	1.05	**0.98**	1.00	1.00	1.04	1.09	1.03	1.01	1.03	1.12	1.02	1.02
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.10	3.55	1.00	0.97	1.12	4.69	0.99	0.96	1.12	3.97	1.00	0.96	1.04	>5	1.02	1.00	0.97	4.27	0.97	**0.95**
			4	1.05	>5	1.00	0.95	1.07	>5	0.98	0.94	1.07	>5	1.00	0.95	0.99	>5	0.98	0.97	0.93	>5	0.92	**0.91**
			8	1.06	>5	1.03	0.99	1.07	>5	1.00	0.97	1.07	>5	1.03	0.99	1.04	>5	0.96	0.98	0.96	>5	0.94	**0.94**
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.09	1.13	1.08	1.03	1.10	1.10	1.08	**1.02**	1.10	1.11	1.08	1.02	1.27	1.25	1.12	1.03	1.11	1.09	1.12	1.06
			4	1.10	1.13	1.10	**1.00**	1.11	1.11	1.09	1.00	1.11	1.12	1.09	1.00	1.24	1.27	1.13	1.02	1.09	1.07	1.13	1.06
			8	1.00	1.05	1.07	0.98	1.02	1.05	1.06	**0.97**	1.02	1.05	1.06	0.98	1.09	1.25	1.04	0.98	1.09	1.06	1.05	1.01
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.11	3.59	1.01	0.96	1.14	3.78	1.01	0.96	1.13	3.55	1.01	0.96	1.39	4.26	1.03	0.99	1.01	4.04	0.98	**0.95**
			4	1.06	>5	1.01	0.95	1.08	>5	1.01	0.94	1.07	>5	1.01	0.95	1.41	>5	0.94	0.92	0.96	>5	0.93	**0.92**
			8	1.06	>5	1.04	0.98	1.07	>5	1.04	0.97	1.07	>5	1.04	0.98	1.23	>5	0.96	0.98	0.98	>5	0.95	**0.95**

Notes: The results show the mean relative MAE of each model and estimator made by iterated method, relative to the MAE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. "Long Lag" stands for $p = 4$, $q = 4$, whereas "Short Lag" stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \mathrm{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\mathrm{UNR}_{it}, \Delta \log \mathrm{XMKT}_{it})'$.

for core inflation whereas for consumer price inflation the addition of observables do not improve the forecasts over the models with only common factors; (v) for simpler models heterogeneous estimators, for larger and more complex models homogeneous estimators perform better.

The analysis in this study brings some important questions. First of all, the factor forecasts can be improved by using targeted predictors in the spirit of Bai and Ng (2008a). As the authors showed, the order of importance of common factors in the predictors is not necessarily the same as their order of importance in terms of their predictive ability for the variable of interest. In this case, the common factor forecasts can be improved by machine learning methods by selecting the most important factors. Secondly, we considered only heterogeneous and homogeneous estimators of the parameters on the right hand side variables. A middle way solution is to consider partially heterogeneous estimators as in the works by Bonhomme and Manresa (2015) and Su et al. (2016). These two points are part of an ongoing research agenda.

Conclusion

The availability of panel data sets with comparable time and individual dimensions is rapidly increasing. The number of questions concerning the optimal ways to estimate the parameters of these models, to draw inference, and make better forecasts using them as well. In this thesis some of these questions are taken into consideration. In the first chapter, estimation, inference and forecasting problems in large, heterogeneous data sets have been considered in a general framework. In the second chapter a hypothesis testing issue is taken into consideration in detail. Namely, novel tests of equal predictive ability hypotheses are developed. Finally, the third chapter has gone further in the optimal forecasting strategies using heterogeneous panel data sets with cross-sectional dependence. Some findings from each chapter are listed below.

Heterogeneity and Cross-Sectional Dependence in Panels. In this chapter, the performance of alternative homogeneous and heterogeneous panel data estimators is evaluated. The comparison was performed using several models with cross-sectional dependence. These dependencies are modeled either by spatial error dependence or common factors or both. These specifications are general enough to compare the cases of weak cross-sectional dependence (WCD) (connected to a spatial weighted matrix) and SCD (common factors). The chapter revisited the literature on the alternative models and estimation procedures accounting for the nature and the degree of cross-sectional dependence. In specific, the performance of sixteen estimators is compared using an extensive Monte Carlo exercise. Also the forecasting performance of each estimator is evaluated. An important contribution is done by suggesting a methodology which makes panel data models with unobserved common factors operational for post-sample prediction.

The main results obtained in the simulation exercise in this chapter can be summarized as follows: (i) Even for small T and n, heterogeneous estimators outperform their homogeneous counterparts, however most of the estimators considered show desirable small sample properties; (ii) the dominance of the heterogeneous estimators are more pronounced for the cases of high heterogeneity, as expected, and this main result holds for different degrees of spatial dependence and factor dependence as well; (iii) the main difference on the performance of the two alternative methods of dealing with unobserved common factors occurs when it is moved from low to high spatial dependence; whereas changing from low to high factor dependence does not make a big difference in their comparative performance; (iv) the performance of partially heterogeneous estimators improves as the number of groups assumed in the estimation increase; (v) the findings listed here are confirmed by the forecasting exercise.

Equal Predictive Ability Tests for Panel Data. This chapter has been concerned with the problem of testing equal predictive ability hypothesis using panel data. The test which is proposed by Diebold and Mariano (1995) has been generalized to a panel data context taking into account the complications arise from using micro and macro data sets. Novel tests which are robust to different forms of cross-sectional dependence are derived, where these dependencies may be arising either from spatial dependence or common factors or both.

The small sample properties of the proposed tests have been found to be satisfactory in a large set of Monte Carlo simulations. In particular, the tests which are robust to strong cross-sectional dependence are found to be correctly sized in all experiments. This is the case even in the experiments which do not involve common factors but only spatial dependence. However, their power is generally low compared to test statistics which are robust only to spatial dependence, given that forecast errors do not contain common factors. In these cases, by means of Monte Carlo evidence particular kernel functions are suggested.

Finally, the tests have been used to compare the prediction performance of the two major organizations, the Organisation for Economic Co-operation and Development (OECD) and IMF, on their historical economic growth forecasts. It is found that IMF has an overall better performance in terms of bias whereas OECD makes predictions with less variance. However, the difference is most of the time statistically insignificant. In a sub-sample of G7 countries OECD predictions are found to be superior to that of IMF.

A possible extension of the testing procedures proposed in this chapter is to allow distinguishing between the sources of the differences in predictive ability. In the chapter it is suggested that the predictive ability of different forecasters may differ through periods while on average they have equal predictive power. To deal with this situation, the conditional EPA tests can be derived in a panel data framework. This is an ongoing research agenda.

Multistep Forecasts with Factor-Augmented Panel Regressions. In this chapter, different strategies of forecasting using panel data are evaluated in terms of their accuracy. The iterated and direct forecasts are compared using a dataset containing twelve quarterly macroeconomic variables from 20 OECD countries. Forecast accuracy measures based on pseudo-out-of-sample forecasts for three different variables are reported. The results showed that (i) only for the models without common factors iterated forecasting scheme is superior to the direct scheme according to all measures of forecast accuracy; (ii) however, lag length selection is much more important in the case of iterative method; misspecification of the model can lead to worse forecasts; (iii) the models with global common factors estimated using principal components methods from the observations on all countries in the sample improves the forecast accuracy considerably; (iv) using indicators in addition to lags of the variables of interest and common factors improves the forecast performance for core inflation whereas for consumer price inflation the addition of observables do not improve the forecasts over the models with only common factors; (v) for simpler models heterogeneous estimators, for larger and more complex models homogeneous estimators perform better.

The analysis in this study brings some important questions. First of all, the factor forecasts can be improved by using targeted predictors in the spirit of Bai and Ng (2008a). As the authors showed, the order of importance of common factors in the predictors is not necessarily the same as their order of importance in terms of their predictive ability for the variable of interest. In this case, the common factor forecasts can be improved by machine learning methods by selecting the most important factors. Secondly, we considered only heterogeneous and homogeneous estimators of the parameters on the right hand side variables. A middle way solution is to consider partially heterogeneous estimators as in the works by Bonhomme and Manresa (2015) and Su et al. (2016). These two points are part of an ongoing research agenda.

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Additional Appendices

Appendix A

Additional Results for Chapter 1

Table A1: Low Heterogeneity – DGP1: No CSD

	Heterogeneous									*Homogeneous*								
T / N	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)				
	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	0.18	-0.11	0.20	0.16	11.58	9.64	9.11	10.11	20	0.12	-0.21	0.28	0.20	11.65	10.01	9.57	10.41
50	0.18	0.22	-0.09	0.16	7.35	5.97	5.68	6.33	50	0.01	0.37	-0.03	0.14	7.32	6.24	5.92	6.49
100	0.05	-0.05	0.16	0.09	5.11	4.25	4.03	4.46	100	-0.01	-0.06	0.18	0.08	5.21	4.50	4.16	4.62
Average	0.13	0.13	0.15	0.14	8.01	6.62	6.27	6.97	Average	0.05	0.21	0.16	0.14	8.06	6.92	6.55	7.18
*SW**									*2WFE*								
20	0.18	-0.14	0.22	0.18	11.04	9.58	9.12	9.91	20	0.30	-0.15	0.21	0.22	13.20	10.84	10.35	11.46
50	0.11	0.25	-0.08	0.15	7.07	5.95	5.68	6.23	50	-0.21	0.17	0.12	0.17	8.14	7.26	7.10	7.50
100	0.01	-0.04	0.17	0.07	4.88	4.24	4.02	4.38	100	-0.07	0.06	0.25	0.12	5.42	5.15	5.04	5.20
Average	0.10	0.14	0.16	0.13	7.66	6.59	6.27	6.84	Average	0.19	0.13	0.19	0.17	8.92	7.75	7.50	8.05
CCEMG									*CCEP*								
20	0.19	-0.08	0.23	0.17	12.65	9.74	9.15	10.51	20	0.03	-0.21	0.29	0.18	12.30	10.10	9.58	10.66
50	0.17	0.24	-0.10	0.17	7.85	6.07	5.70	6.54	50	-0.05	0.40	-0.05	0.17	7.64	6.35	5.90	6.63
100	0.09	-0.05	0.16	0.10	5.47	4.31	4.04	4.61	100	0.01	-0.08	0.19	0.09	5.50	4.58	4.18	4.75
Average	0.15	0.13	0.16	0.15	8.65	6.71	6.30	7.22	Average	0.03	0.23	0.18	0.14	8.48	7.01	6.55	7.35
CCEMGX									*CCEPX*								
20	0.26	-0.10	0.20	0.19	12.90	9.74	9.16	10.60	20	-0.02	-0.19	0.27	0.16	12.44	10.14	9.61	10.73
50	0.17	0.25	-0.11	0.17	7.93	6.07	5.71	6.57	50	-0.05	0.40	-0.05	0.17	7.67	6.33	5.91	6.64
100	0.08	-0.04	0.16	0.09	5.50	4.31	4.04	4.62	100	-0.02	-0.07	0.19	0.09	5.47	4.58	4.19	4.74
Average	0.17	0.13	0.16	0.15	8.78	6.70	6.30	7.26	Average	0.03	0.22	0.17	0.14	8.52	7.02	6.57	7.37
IPCMG									*IPCP*								
20	0.21	-0.20	0.13	0.18	16.15	10.17	9.23	11.85	20	0.32	-0.17	0.34	0.28	13.29	10.69	10.24	11.41
50	0.13	0.23	-0.08	0.15	8.09	6.14	5.73	6.65	50	0.03	0.33	-0.05	0.13	7.88	6.50	6.02	6.80
100	0.04	-0.04	0.16	0.08	5.59	4.32	4.05	4.65	100	0.06	-0.14	0.20	0.14	5.61	4.59	4.19	4.80
Average	0.13	0.16	0.12	0.14	9.94	6.87	6.34	7.72	Average	0.13	0.21	0.20	0.18	8.93	7.26	6.82	7.67
PCMGX									*PCPX*								
20	0.11	-0.04	0.21	0.12	13.64	10.01	9.20	10.95	20	0.03	-0.20	0.21	0.15	13.01	10.57	9.58	11.05
50	0.16	0.24	-0.05	0.15	8.15	6.25	5.74	6.71	50	0.02	0.38	-0.03	0.15	7.91	6.56	5.98	6.82
100	0.11	-0.02	0.18	0.10	5.90	4.36	4.05	4.77	100	0.05	-0.10	0.21	0.12	5.74	4.62	4.23	4.86
Average	0.13	0.10	0.15	0.12	9.23	6.87	6.33	7.48	Average	0.04	0.23	0.15	0.14	8.89	7.25	6.59	7.58
PCMGX2S									*PCPX2S*								
20	0.11	-0.14	0.18	0.14	14.60	10.17	9.22	11.33	20	0.31	-0.18	0.23	0.24	13.93	10.82	10.06	11.60
50	0.13	0.21	-0.04	0.13	8.55	6.34	5.76	6.88	50	-0.02	0.36	-0.05	0.15	8.32	6.71	6.06	7.03
100	0.14	-0.02	0.18	0.11	6.21	4.42	4.08	4.90	100	0.07	-0.15	0.22	0.15	6.05	4.68	4.24	4.99
Average	0.13	0.13	0.13	0.13	9.79	6.98	6.35	7.71	Average	0.13	0.23	0.16	0.18	9.43	7.40	6.79	7.87
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	7.30	6.05	6.30	6.55	12.70	17.70	19.50	16.63	20	6.25	6.50	7.30	6.68	14.00	17.10	17.65	16.25
50	6.10	4.95	5.80	5.62	30.00	40.35	39.45	36.60	50	5.45	5.25	5.80	5.50	28.90	37.30	38.10	34.77
100	4.80	6.05	5.45	5.43	49.80	62.70	69.25	60.58	100	4.90	5.65	5.20	5.25	47.90	59.65	68.10	58.55
Average	6.07	5.68	5.85	5.87	30.83	40.25	42.73	37.94	Average	5.53	5.80	6.10	5.81	30.27	38.02	41.28	36.52
*SW**									*2WFE*								
20	7.70	6.60	6.55	6.95	13.15	17.45	19.70	16.77	20	40.70	52.05	68.65	53.80	13.00	16.10	16.80	15.30
50	6.80	4.85	5.75	5.80	30.60	42.35	39.85	37.60	50	39.95	53.90	70.40	54.75	21.65	28.70	31.95	27.43
100	5.85	6.15	5.45	5.82	51.50	62.70	68.90	61.03	100	35.80	58.25	70.10	54.72	45.25	47.60	52.40	48.42
Average	6.78	5.87	5.92	6.19	31.75	40.83	42.82	38.47	Average	38.82	54.73	69.72	54.42	26.63	30.80	33.72	30.38
CCEMG									*CCEP*								
20	7.30	7.15	7.35	7.27	12.50	17.25	19.75	16.50	20	8.50	7.70	9.10	8.43	12.20	15.55	18.10	15.28
50	6.05	5.50	6.05	5.87	26.75	38.45	39.15	34.78	50	5.95	5.90	6.20	6.02	24.90	35.80	37.75	32.82
100	5.10	5.80	5.65	5.52	46.15	62.30	69.70	59.38	100	5.20	5.95	5.25	5.47	45.95	57.60	68.55	57.37
Average	6.15	6.15	6.35	6.22	28.47	39.33	42.87	36.89	Average	6.55	6.52	6.85	6.64	27.68	36.32	41.47	35.16
CCEMGX									*CCEPX*								
20	6.55	5.95	6.50	6.33	11.65	18.00	19.15	16.27	20	6.75	6.50	7.55	6.93	12.55	15.80	17.55	15.30
50	6.30	5.00	6.00	5.77	24.75	39.45	39.00	34.40	50	5.80	5.25	5.80	5.62	25.45	36.50	38.10	33.35
100	5.60	5.55	5.70	5.62	43.20	62.85	69.35	58.47	100	4.55	5.70	5.05	5.10	45.55	57.60	67.85	57.00
Average	6.15	5.50	6.07	5.91	26.53	40.10	42.50	36.38	Average	5.70	5.82	6.13	5.88	27.85	36.63	41.17	35.22
IPCMG									*IPCP*								
20	6.35	6.25	6.50	6.37	10.40	14.90	19.45	14.92	20	7.30	9.35	10.65	9.10	11.30	14.40	17.65	14.45
50	4.85	5.50	6.00	5.45	25.10	37.40	39.60	34.03	50	6.60	7.20	7.35	7.05	24.55	34.15	37.05	31.92
100	4.75	5.80	5.20	5.25	44.30	61.35	69.55	58.40	100	6.40	7.05	6.20	6.55	42.60	56.70	67.30	55.53
Average	5.32	5.85	5.90	5.69	26.60	37.88	42.87	35.78	Average	6.77	7.87	8.07	7.57	26.15	35.08	40.67	33.97
PCMGX									*PCPX*								
20	7.35	6.30	6.30	6.65	10.25	17.45	19.35	15.68	20	7.40	6.70	7.45	7.18	11.85	14.95	18.05	14.95
50	6.15	5.45	6.10	5.90	23.60	36.50	38.65	32.92	50	5.60	5.70	5.70	5.67	25.25	34.90	37.65	32.60
100	5.15	5.75	5.40	5.43	39.40	61.15	68.65	56.40	100	5.65	6.00	5.20	5.62	41.45	55.95	67.30	54.90
Average	6.22	5.83	5.93	5.99	24.42	38.37	42.22	35.00	Average	6.22	6.13	6.12	6.16	26.18	35.27	41.00	34.15
PCMGX2S									*PCPX2S*								
20	6.80	6.75	6.10	6.55	9.85	15.80	19.40	15.02	20	8.65	8.70	9.90	9.08	10.45	15.00	16.10	13.85
50	6.15	5.00	6.10	5.75	20.90	37.80	38.10	32.27	50	6.80	7.05	6.55	6.80	22.70	31.95	37.95	30.87
100	4.95	5.65	5.25	5.28	37.65	60.10	69.25	55.67	100	6.30	7.15	5.60	6.35	38.80	50.90	67.45	52.38
Average	5.97	5.80	5.82	5.86	22.80	37.90	42.25	34.32	Average	7.25	7.63	7.35	7.41	23.98	32.62	40.50	32.37

Table A2: Low Heterogeneity – DGP2, Case a: Low Spatial Dependence

	Heterogeneous									*Homogeneous*							
T / N	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	-0.06	-0.14	-0.32	0.18	11.23	9.43	8.90	9.85	20	0.13	-0.17	-0.29	0.19	11.47	9.87	9.09	10.14
50	-0.18	0.19	-0.20	0.19	6.97	5.86	5.55	6.13	50	-0.18	0.19	-0.21	0.19	7.22	6.10	5.78	6.36
100	-0.18	-0.11	0.11	0.13	5.04	4.18	4.09	4.44	100	-0.16	-0.15	0.08	0.13	5.13	4.38	4.18	4.56
Average	0.14	0.14	0.21	0.17	7.74	6.49	6.18	6.81	Average	0.16	0.17	0.19	0.17	7.94	6.78	6.35	7.02
*SW**									*2WFE*								
20	0.07	-0.13	-0.31	0.17	10.95	9.40	8.90	9.75	20	0.40	0.11	-0.27	0.26	13.37	11.21	9.99	11.52
50	-0.19	0.19	-0.20	0.19	6.73	5.85	5.55	6.04	50	-0.20	0.24	-0.31	0.25	7.69	7.22	7.08	7.33
100	-0.17	-0.11	0.11	0.13	4.87	4.17	4.09	4.38	100	-0.14	-0.09	0.07	0.10	5.37	5.08	4.72	5.06
Average	0.14	0.14	0.21	0.16	7.52	6.48	6.18	6.72	Average	0.25	0.15	0.22	0.20	8.81	7.84	7.26	7.97
CCEMG									*CCEP*								
20	0.14	-0.12	-0.29	0.18	12.13	9.51	8.92	10.19	20	0.23	-0.14	-0.28	0.22	12.07	9.95	9.11	10.38
50	-0.14	0.16	-0.21	0.17	7.47	5.91	5.56	6.32	50	-0.15	0.20	-0.21	0.19	7.55	6.15	5.79	6.50
100	-0.10	-0.12	0.11	0.11	5.37	4.23	4.11	4.57	100	-0.14	-0.16	0.08	0.13	5.36	4.41	4.20	4.66
Average	0.13	0.13	0.20	0.16	8.32	6.55	6.20	7.02	Average	0.17	0.17	0.19	0.18	8.33	6.84	6.37	7.18
CCEMGX									*CCEPX*								
20	0.26	-0.09	-0.30	0.22	12.24	9.55	8.89	10.23	20	0.33	-0.14	-0.27	0.25	12.11	9.96	9.09	10.39
50	-0.17	0.18	-0.22	0.19	7.48	5.92	5.55	6.32	50	-0.15	0.20	-0.21	0.19	7.58	6.15	5.78	6.51
100	-0.13	-0.12	0.10	0.12	5.46	4.23	4.12	4.60	100	-0.13	-0.15	0.08	0.12	5.38	4.42	4.20	4.67
Average	0.19	0.13	0.21	0.17	8.39	6.57	6.19	7.05	Average	0.20	0.17	0.19	0.18	8.36	6.84	6.36	7.19
IPCMG									*IPCP*								
20	-0.02	-0.12	-0.34	0.16	13.87	9.86	9.05	10.93	20	0.02	-0.23	-0.40	0.22	12.94	10.48	9.64	11.02
50	-0.29	0.20	-0.20	0.23	7.96	5.97	5.59	6.51	50	-0.01	0.21	-0.20	0.14	7.66	6.34	5.94	6.65
100	-0.17	-0.08	0.11	0.12	5.46	4.25	4.10	4.60	100	-0.15	-0.16	0.08	0.13	5.42	4.46	4.24	4.71
Average	0.16	0.14	0.22	0.17	9.10	6.69	6.25	7.35	Average	0.06	0.20	0.23	0.16	8.67	7.09	6.61	7.46
PCMGX									*PCPX*								
20	-0.05	-0.18	-0.33	0.19	12.76	9.61	8.97	10.45	20	0.02	-0.26	-0.26	0.18	12.48	10.06	9.23	10.59
50	-0.17	0.19	-0.19	0.18	7.74	5.98	5.57	6.43	50	-0.07	0.19	-0.21	0.16	7.70	6.25	5.82	6.59
100	-0.24	-0.16	0.10	0.17	5.74	4.32	4.11	4.72	100	-0.26	-0.17	0.10	0.18	5.64	4.47	4.21	4.77
Average	0.15	0.17	0.21	0.18	8.75	6.64	6.22	7.20	Average	0.12	0.21	0.19	0.17	8.61	6.93	6.42	7.32
PCMGX2S									*PCPX2S*								
20	0.01	-0.19	-0.34	0.18	13.44	9.65	9.00	10.70	20	0.02	-0.22	-0.36	0.20	13.24	10.43	9.49	11.05
50	-0.20	0.20	-0.20	0.20	8.30	6.05	5.59	6.65	50	0.04	0.18	-0.22	0.15	8.05	6.42	5.95	6.81
100	-0.23	-0.13	0.10	0.15	6.04	4.36	4.11	4.84	100	-0.25	-0.16	0.08	0.16	5.92	4.55	4.26	4.91
Average	0.15	0.17	0.21	0.18	9.26	6.69	6.23	7.39	Average	0.10	0.19	0.22	0.17	9.07	7.13	6.57	7.59
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	5.65	6.40	6.60	6.22	14.65	17.55	18.05	16.75	20	6.50	6.95	6.30	6.58	13.25	16.20	18.00	15.82
50	5.15	5.50	4.50	5.05	28.90	39.20	41.50	36.53	50	5.40	5.25	5.40	5.35	28.30	36.40	37.60	34.10
100	4.80	5.05	5.85	5.23	50.65	64.90	68.00	61.18	100	5.15	5.45	5.45	5.35	48.35	59.35	65.70	57.80
Average	5.20	5.65	5.65	5.50	31.40	40.55	42.52	38.16	Average	5.68	5.88	5.72	5.76	29.97	37.32	40.43	35.91
*SW**									*2WFE*								
20	6.50	6.85	6.70	6.68	14.05	16.90	17.10	16.02	20	39.95	55.65	64.45	53.35	12.85	14.75	16.00	14.53
50	5.70	5.20	4.65	5.18	30.75	40.15	41.80	37.57	50	37.70	55.50	71.65	54.95	24.90	29.20	28.85	27.65
100	5.65	5.20	5.95	5.60	53.15	65.10	67.90	62.05	100	36.60	56.45	66.35	53.13	44.50	47.60	56.85	49.65
Average	5.95	5.75	5.77	5.82	32.65	40.72	42.27	38.54	Average	38.08	55.87	67.48	53.81	27.42	30.52	33.90	30.61
CCEMG									*CCEP*								
20	7.20	7.80	7.55	7.52	12.20	16.55	17.15	15.30	20	7.20	8.85	8.05	8.03	11.75	15.70	18.80	15.42
50	6.25	5.90	4.90	5.68	25.55	37.45	42.25	35.08	50	6.65	5.80	5.75	6.07	23.65	34.65	37.00	31.77
100	5.05	5.05	6.25	5.45	46.15	63.80	68.40	59.45	100	5.25	5.65	5.65	5.52	45.50	58.45	66.55	56.83
Average	6.17	6.25	6.23	6.22	27.97	39.27	42.60	36.61	Average	6.37	6.77	6.48	6.54	26.97	36.27	40.78	34.67
CCEMGX									*CCEPX*								
20	6.45	6.65	5.95	6.35	11.80	16.95	18.00	15.58	20	6.05	6.90	6.15	6.37	13.00	15.30	18.45	15.58
50	5.25	5.35	4.45	5.02	25.80	38.60	41.75	35.38	50	6.75	4.95	5.60	5.77	22.45	37.10	36.85	32.13
100	5.25	5.00	5.85	5.37	44.25	64.00	67.75	58.67	100	4.85	5.30	5.35	5.17	46.05	58.95	66.05	57.02
Average	5.65	5.67	5.42	5.58	27.28	39.85	42.50	36.54	Average	5.88	5.72	5.70	5.77	27.17	37.12	40.45	34.91
IPCMG									*IPCP*								
20	4.95	6.45	6.15	5.85	13.30	16.90	18.25	16.15	20	7.50	9.75	8.45	8.57	11.95	15.90	17.85	15.23
50	5.35	5.75	5.20	5.43	24.00	38.20	39.50	33.90	50	6.00	7.40	7.00	6.80	27.20	34.50	37.20	32.97
100	5.40	4.55	5.50	5.15	43.50	66.10	68.55	59.38	100	6.50	6.35	6.45	6.43	43.00	57.65	66.20	55.62
Average	5.23	5.58	5.62	5.48	26.93	40.40	42.10	36.48	Average	6.67	7.83	7.30	7.27	27.38	36.02	40.42	34.61
PCMGX									*PCPX*								
20	6.20	6.80	6.80	6.60	11.20	15.65	18.40	15.08	20	6.65	6.65	6.20	6.50	12.20	15.65	17.55	15.13
50	5.15	5.15	4.60	4.97	25.15	38.50	41.60	35.08	50	5.55	4.85	5.30	5.23	26.15	37.30	37.50	33.65
100	4.80	5.00	5.55	5.12	42.95	62.10	68.85	57.97	100	5.30	4.75	5.30	5.12	41.60	58.70	66.90	55.73
Average	5.38	5.65	5.65	5.56	26.43	38.75	42.95	36.04	Average	5.83	5.42	5.60	5.62	26.65	37.22	40.65	34.84
PCMGX2S									*PCPX2S*								
20	6.15	6.30	6.45	6.30	10.90	16.10	18.20	15.07	20	8.50	8.40	7.55	8.15	10.40	15.90	18.40	14.90
50	5.50	5.45	4.75	5.23	21.85	37.15	40.55	33.18	50	6.80	7.10	6.30	6.73	25.10	36.35	38.55	33.33
100	5.05	4.75	5.10	4.97	37.35	62.30	69.75	56.47	100	6.15	5.55	6.15	5.95	38.35	57.45	66.40	54.07
Average	5.57	5.50	5.43	5.50	23.37	38.52	42.83	34.91	Average	7.15	7.02	6.67	6.94	24.62	36.57	41.12	34.10

Table A3: Low Heterogeneity – DGP2, Case *b*: High Spatial Dependence

	Heterogeneous									*Homogeneous*							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	-0.29	-0.17	-0.42	0.29	15.84	10.56	9.59	12.00	20	0.08	-0.19	-0.38	0.22	14.78	10.80	9.71	11.76
50	-0.32	0.18	-0.21	0.24	8.90	6.67	5.88	7.15	50	-0.30	0.18	-0.20	0.23	8.59	6.81	6.08	7.16
100	-0.24	-0.12	0.16	0.17	6.36	4.69	4.31	5.12	100	-0.21	-0.16	0.12	0.16	6.04	4.79	4.38	5.07
Average	0.29	0.16	0.26	0.24	10.37	7.31	6.59	8.09	Average	0.20	0.17	0.23	0.20	9.80	7.46	6.72	8.00
*SW**									*2WFE*								
20	-0.07	-0.14	-0.40	0.20	14.60	10.49	9.58	11.56	20	0.46	0.12	-0.31	0.30	14.48	11.46	10.09	12.01
50	-0.34	0.19	-0.22	0.25	8.35	6.60	5.87	6.94	50	-0.24	0.27	-0.31	0.27	8.31	7.52	7.20	7.68
100	-0.18	-0.14	0.15	0.15	5.99	4.65	4.30	4.98	100	-0.16	-0.11	0.09	0.12	5.79	5.24	4.83	5.29
Average	0.19	0.16	0.26	0.20	9.65	7.25	6.58	7.82	Average	0.28	0.17	0.24	0.23	9.53	8.07	7.37	8.32
CCEMG									*CCEP*								
20	0.15	-0.13	-0.33	0.20	15.09	10.12	9.25	11.49	20	0.33	-0.17	-0.31	0.27	14.27	10.45	9.38	11.36
50	-0.23	0.15	-0.23	0.20	9.47	6.62	5.84	7.31	50	-0.23	0.19	-0.22	0.21	8.92	6.76	6.05	7.24
100	-0.11	-0.15	0.14	0.13	6.88	4.71	4.32	5.30	100	-0.17	-0.18	0.10	0.15	6.33	4.79	4.40	5.18
Average	0.16	0.14	0.23	0.18	10.48	7.15	6.47	8.03	Average	0.24	0.18	0.21	0.21	9.84	7.33	6.61	7.93
CCEMGX									*CCEPX*								
20	0.22	-0.09	-0.34	0.22	16.47	10.30	9.27	12.01	20	0.43	-0.14	-0.32	0.30	14.30	10.48	9.38	11.38
50	-0.30	0.19	-0.24	0.24	9.61	6.67	5.83	7.37	50	-0.23	0.21	-0.22	0.22	8.93	6.76	6.04	7.24
100	-0.16	-0.15	0.13	0.15	7.04	4.76	4.33	5.38	100	-0.13	-0.18	0.11	0.14	6.34	4.82	4.41	5.19
Average	0.23	0.14	0.24	0.20	11.04	7.24	6.48	8.25	Average	0.27	0.17	0.21	0.22	9.86	7.35	6.61	7.94
IPCMG									*IPCP*								
20	-0.28	-0.15	-0.33	0.25	13.48	9.80	9.08	10.79	20	0.07	-0.21	-0.32	0.20	12.97	10.21	9.29	10.82
50	-0.23	0.15	-0.25	0.21	8.71	6.35	5.80	6.95	50	-0.20	0.19	-0.25	0.22	8.26	6.55	6.02	6.94
100	-0.21	-0.17	0.14	0.17	6.36	4.62	4.27	5.08	100	-0.10	-0.21	0.10	0.14	6.05	4.75	4.37	5.06
Average	0.24	0.16	0.24	0.21	9.51	6.92	6.39	7.61	Average	0.13	0.20	0.22	0.18	9.09	7.17	6.56	7.61
PCMGX									*PCPX*								
20	-0.50	-0.21	-0.42	0.38	19.37	11.12	9.84	13.44	20	-0.10	-0.28	-0.34	0.24	17.24	11.22	9.99	12.82
50	-0.30	0.21	-0.18	0.23	10.42	6.96	5.97	7.78	50	-0.15	0.20	-0.21	0.19	9.43	7.09	6.16	7.56
100	-0.32	-0.21	0.15	0.23	7.73	4.99	4.36	5.70	100	-0.32	-0.19	0.14	0.22	6.91	4.98	4.45	5.44
Average	0.37	0.21	0.25	0.28	12.51	7.69	6.73	8.97	Average	0.19	0.22	0.23	0.21	11.19	7.76	6.87	8.61
PCMGX2S									*PCPX2S*								
20	-0.11	-0.21	-0.35	0.22	16.10	10.13	9.19	11.81	20	-0.09	-0.32	-0.29	0.23	14.36	10.46	9.41	11.41
50	-0.26	0.18	-0.23	0.22	10.07	6.61	5.84	7.51	50	-0.08	0.21	-0.25	0.18	9.02	6.77	6.07	7.29
100	-0.31	-0.23	0.13	0.23	7.63	4.90	4.32	5.62	100	-0.21	-0.23	0.12	0.19	6.80	4.92	4.42	5.38
Average	0.23	0.21	0.24	0.22	11.26	7.21	6.45	8.31	Average	0.13	0.25	0.22	0.20	10.06	7.38	6.63	8.03
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	5.45	6.70	6.35	6.17	9.65	14.60	17.00	13.75	20	6.50	6.75	6.25	6.50	9.15	14.85	15.70	13.23
50	4.55	5.35	4.55	4.82	21.80	33.60	37.40	30.93	50	5.20	5.10	5.35	5.22	22.10	32.00	34.30	29.47
100	4.65	4.20	5.70	4.85	34.85	57.20	63.45	51.83	100	4.65	5.00	5.50	5.05	37.75	52.35	61.65	50.58
Average	4.88	5.42	5.53	5.28	22.10	35.13	39.28	32.17	Average	5.45	5.62	5.70	5.59	23.00	33.07	37.22	31.09
*SW**									*2WFE*								
20	2.95	7.00	6.35	5.43	10.45	14.90	16.25	13.87	20	30.55	47.50	56.00	44.68	11.65	14.40	15.10	13.72
50	5.35	5.25	4.80	5.13	22.15	34.00	36.40	30.85	50	26.45	42.35	60.85	43.22	22.00	27.75	28.05	25.93
100	6.25	5.05	5.60	5.63	37.40	55.40	62.75	51.85	100	25.35	42.15	54.45	40.65	39.10	45.70	54.35	46.38
Average	4.85	5.77	5.58	5.40	23.33	34.77	38.47	32.19	Average	27.45	44.00	57.10	42.85	24.25	29.28	32.50	28.68
CCEMG									*CCEP*								
20	6.90	8.15	7.05	7.37	10.25	15.55	16.55	14.12	20	7.95	8.30	7.30	7.85	11.00	15.65	17.60	14.75
50	5.95	6.10	5.15	5.73	18.70	31.15	38.20	29.35	50	6.55	5.75	6.00	6.10	20.15	29.60	34.90	28.22
100	5.50	4.90	5.75	5.38	29.90	56.15	64.00	50.02	100	5.55	5.35	5.30	5.40	33.75	51.90	63.05	49.57
Average	6.12	6.38	5.98	6.16	19.62	34.28	39.58	31.16	Average	6.68	6.47	6.20	6.45	21.63	32.38	38.52	30.84
CCEMGX									*CCEPX*								
20	3.50	5.25	5.00	4.58	9.75	15.55	17.15	14.15	20	3.50	5.65	5.15	4.77	11.20	14.00	17.00	14.07
50	4.45	4.80	4.85	4.70	18.90	33.00	36.40	29.43	50	5.90	4.60	5.30	5.27	16.25	31.20	34.70	27.38
100	4.45	4.65	5.40	4.83	30.05	54.50	63.85	49.47	100	4.30	4.60	5.00	4.63	35.60	52.40	63.05	50.35
Average	4.13	4.90	5.08	4.71	19.57	34.35	39.13	31.02	Average	4.57	4.95	5.15	4.89	21.02	32.53	38.25	30.60
IPCMG									*IPCP*								
20	6.65	6.55	6.75	6.65	10.05	15.30	18.25	14.53	20	6.10	6.80	6.65	6.52	11.20	16.65	16.45	14.77
50	6.20	5.65	4.90	5.58	18.95	33.05	38.90	30.30	50	6.40	5.60	5.55	5.85	20.55	31.25	35.75	29.18
100	4.75	5.15	5.50	5.13	34.40	54.60	64.00	51.00	100	5.00	5.55	5.15	5.23	39.15	51.85	63.05	51.35
Average	5.87	5.78	5.72	5.79	21.13	34.32	40.38	31.94	Average	5.83	5.98	5.78	5.87	23.63	33.25	38.42	31.77
PCMGX									*PCPX*								
20	5.85	6.65	6.00	6.17	8.45	12.95	16.50	12.63	20	5.95	6.65	6.10	6.23	8.45	14.10	15.00	12.52
50	5.15	5.30	4.75	5.07	16.45	30.05	37.60	28.03	50	5.05	5.15	5.60	5.27	18.75	29.85	33.30	27.30
100	5.00	5.20	5.65	5.28	25.00	49.80	62.30	45.70	100	5.25	5.05	4.75	5.02	30.15	49.00	64.40	47.85
Average	5.33	5.72	5.47	5.51	16.63	30.93	38.80	28.79	Average	5.42	5.62	5.48	5.51	19.12	30.98	37.57	29.22
PCMGX2S									*PCPX2S*								
20	5.85	6.40	6.40	6.22	11.05	15.00	17.35	14.47	20	7.45	6.45	6.30	6.73	8.60	14.05	17.70	13.45
50	5.65	5.90	4.75	5.43	16.00	32.15	38.30	28.82	50	5.70	5.50	5.25	5.48	19.75	31.45	36.90	29.37
100	5.25	5.30	5.80	5.45	24.90	51.00	62.85	46.25	100	5.20	5.35	5.45	5.33	31.65	49.65	62.05	47.78
Average	5.58	5.87	5.65	5.70	17.32	32.72	39.50	29.84	Average	6.12	5.77	5.67	5.85	20.00	31.72	38.88	30.20

Table A4: Low Heterogeneity – DGP3, Case *c*: Low Factor Dependence

	Heterogeneous									*Homogeneous*							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	18.80	17.72	17.49	18.00	25.13	21.96	21.18	22.76	20	22.67	22.18	22.48	22.44	28.84	26.51	26.37	27.24
50	18.24	17.28	17.32	17.61	21.47	19.28	19.03	19.93	50	21.94	22.05	22.21	22.07	25.42	24.28	24.13	24.61
100	18.11	17.83	17.50	17.81	20.30	19.09	18.42	19.27	100	22.37	22.51	22.35	22.41	25.15	24.05	23.48	24.23
Average	18.38	17.61	17.44	17.81	22.30	20.11	19.54	20.65	Average	22.33	22.24	22.35	22.31	26.47	24.95	24.66	25.36
*SW**									*2WFE*								
20	20.07	18.30	17.82	18.73	25.71	22.35	21.44	23.17	20	0.11	-0.09	0.39	0.20	12.82	11.77	10.92	11.84
50	19.29	17.91	17.63	18.28	22.27	19.84	19.32	20.48	50	-0.14	-0.11	0.16	0.14	8.09	7.09	7.10	7.42
100	19.33	18.42	17.82	18.52	21.43	19.65	18.73	19.94	100	-0.02	0.10	-0.18	0.10	5.55	5.29	4.91	5.25
Average	19.56	18.21	17.76	18.51	23.14	20.61	19.83	21.19	Average	0.09	0.10	0.24	0.14	8.82	8.05	7.64	8.17
CCEMG									*CCEP*								
20	-0.04	-0.03	0.23	0.10	11.98	9.69	9.16	10.28	20	0.17	-0.03	0.25	0.15	12.23	10.20	9.58	10.67
50	-0.21	-0.20	0.07	0.16	7.68	6.04	5.74	6.49	50	-0.29	-0.17	0.16	0.21	7.76	6.34	5.93	6.68
100	-0.09	0.14	-0.10	0.11	5.37	4.33	3.94	4.55	100	-0.05	0.08	-0.14	0.09	5.38	4.52	4.06	4.65
Average	0.11	0.12	0.13	0.12	8.34	6.69	6.28	7.10	Average	0.17	0.10	0.18	0.15	8.46	7.02	6.52	7.33
CCEMGX									*CCEPX*								
20	0.08	-0.06	0.23	0.12	12.23	9.67	9.16	10.36	20	0.14	-0.06	0.24	0.15	12.23	10.19	9.58	10.67
50	-0.19	-0.19	0.06	0.15	7.76	6.03	5.74	6.51	50	-0.29	-0.16	0.15	0.20	7.79	6.33	5.93	6.68
100	-0.07	0.15	-0.10	0.11	5.38	4.34	3.94	4.55	100	-0.05	0.08	-0.15	0.09	5.38	4.52	4.05	4.65
Average	0.12	0.13	0.13	0.13	8.45	6.68	6.28	7.14	Average	0.16	0.10	0.18	0.15	8.47	7.01	6.52	7.33
IPCMG									*IPCP*								
20	0.35	0.07	0.28	0.23	13.65	9.74	9.16	10.85	20	-0.56	-0.53	0.07	0.38	12.82	11.24	10.30	11.46
50	0.05	-0.11	0.06	0.07	7.57	5.90	5.68	6.39	50	-0.62	-0.53	-0.06	0.40	7.97	6.88	6.58	7.15
100	-0.09	0.13	-0.05	0.09	5.11	4.26	3.91	4.42	100	-0.39	-0.16	-0.27	0.27	5.54	5.01	4.59	5.05
Average	0.16	0.10	0.13	0.13	8.78	6.63	6.25	7.22	Average	0.52	0.40	0.13	0.35	8.78	7.71	7.16	7.88
PCMGX									*PCPX*								
20	1.34	0.39	0.38	0.70	16.14	10.92	9.63	12.23	20	1.09	0.28	0.35	0.58	14.85	11.11	9.80	11.92
50	0.61	0.06	0.11	0.26	9.75	6.65	6.03	7.48	50	0.28	0.01	0.18	0.16	9.09	6.76	6.17	7.34
100	0.46	0.28	-0.06	0.26	6.78	4.92	4.17	5.29	100	0.26	0.19	-0.11	0.19	6.36	4.98	4.25	5.20
Average	0.80	0.24	0.18	0.41	10.89	7.50	6.61	8.33	Average	0.54	0.16	0.21	0.31	10.10	7.62	6.74	8.15
PCMGX2S									*PCPX2S*								
20	0.55	0.08	0.35	0.33	13.53	9.80	9.17	10.83	20	0.13	-0.05	0.23	0.13	12.97	10.31	9.41	10.90
50	0.11	-0.15	0.09	0.12	8.33	6.06	5.74	6.71	50	-0.27	-0.18	0.11	0.19	8.09	6.35	5.90	6.78
100	0.03	0.18	-0.07	0.09	5.59	4.37	3.96	4.64	100	-0.08	0.10	-0.14	0.10	5.47	4.54	4.09	4.70
Average	0.23	0.14	0.17	0.18	9.15	6.74	6.29	7.39	Average	0.16	0.11	0.16	0.14	8.84	7.07	6.47	7.46
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	26.80	31.70	36.30	31.60	13.40	15.90	19.90	16.40	20	34.65	38.80	44.30	39.25	12.90	14.95	16.55	14.80
50	50.20	61.70	64.50	58.80	22.25	28.90	31.30	27.48	50	60.65	69.25	74.45	68.12	20.05	23.70	27.35	23.70
100	71.95	86.30	90.35	82.87	34.10	43.60	53.00	43.57	100	80.55	90.90	94.30	88.58	25.55	31.80	37.25	31.53
Average	49.65	59.90	63.72	57.76	23.25	29.47	34.73	29.15	Average	58.62	66.32	71.02	65.32	19.50	23.48	27.05	23.34
*SW**									*2WFE*								
20	30.30	33.85	37.45	33.87	13.45	16.35	19.20	16.33	20	44.20	57.50	69.90	57.20	13.20	12.55	16.20	13.98
50	57.40	64.40	66.50	62.77	21.50	29.60	30.25	27.12	50	40.75	57.35	69.95	56.02	22.40	26.65	29.90	26.32
100	78.45	88.95	91.05	86.15	34.55	44.50	52.50	43.85	100	42.50	60.50	68.90	57.30	42.25	47.20	50.70	46.72
Average	55.38	62.40	65.00	60.93	23.17	30.15	33.98	29.10	Average	42.48	58.45	69.58	56.84	25.95	28.80	32.27	29.01
CCEMG									*CCEP*								
20	6.00	7.80	7.90	7.23	14.80	16.15	20.15	17.03	20	7.70	7.35	8.10	7.72	14.25	15.55	18.25	16.02
50	6.05	6.05	6.85	6.32	22.85	34.65	39.00	32.17	50	6.40	5.85	6.50	6.25	23.35	34.20	38.00	31.85
100	4.95	6.10	5.60	5.55	46.45	62.70	68.55	59.23	100	5.75	5.95	5.15	5.62	44.40	59.30	67.00	56.90
Average	5.67	6.65	6.78	6.37	28.03	37.83	42.57	36.14	Average	6.62	6.38	6.58	6.53	27.33	36.35	41.08	34.92
CCEMGX									*CCEPX*								
20	5.10	6.30	6.30	5.90	14.60	16.80	20.40	17.27	20	6.70	6.20	6.65	6.52	12.65	15.35	17.75	15.25
50	5.90	5.50	6.40	5.93	23.30	34.85	38.90	32.35	50	6.00	5.65	6.00	5.88	22.95	34.05	37.45	31.48
100	4.60	6.10	5.35	5.35	47.70	63.40	68.35	59.82	100	5.65	5.60	4.90	5.38	44.55	59.85	67.30	57.23
Average	5.20	5.97	6.02	5.73	28.53	38.35	42.55	36.48	Average	6.12	5.82	5.85	5.93	26.72	36.42	40.83	34.66
IPCMG									*IPCP*								
20	5.85	6.20	6.90	6.32	12.80	17.40	19.00	16.40	20	7.55	9.55	10.05	9.05	11.45	13.85	15.35	13.55
50	5.65	5.70	5.95	5.77	25.80	36.80	40.05	34.22	50	6.95	6.70	7.65	7.10	20.95	29.00	30.25	26.73
100	5.25	5.65	5.40	5.43	50.10	64.25	69.30	61.22	100	6.55	6.30	6.10	6.32	41.00	50.50	55.20	48.90
Average	5.58	5.85	6.08	5.84	29.57	39.48	42.78	37.28	Average	7.02	7.52	7.93	7.49	24.47	31.12	33.60	29.73
PCMGX									*PCPX*								
20	6.30	6.50	6.35	6.38	10.55	14.50	19.35	14.80	20	6.40	6.15	6.50	6.35	11.25	14.20	18.10	14.52
50	5.75	4.95	5.60	5.43	18.85	32.10	36.10	29.02	50	5.45	5.05	5.20	5.23	20.45	30.65	37.35	29.48
100	5.10	5.35	4.50	4.98	34.25	53.85	65.10	51.07	100	5.40	5.50	4.55	5.15	35.40	51.55	62.90	49.95
Average	5.72	5.60	5.48	5.60	21.22	33.48	40.18	31.63	Average	5.75	5.57	5.42	5.58	22.37	32.13	39.45	31.32
PCMGX2S									*PCPX2S*								
20	6.05	6.60	6.90	6.52	10.95	16.10	19.10	15.38	20	6.70	7.50	7.25	7.15	12.60	14.20	19.55	15.45
50	5.65	5.55	5.80	5.67	22.20	35.65	38.85	32.23	50	6.60	5.75	6.45	6.27	21.90	33.80	37.55	31.08
100	4.90	5.80	5.25	5.32	44.40	62.65	68.15	58.40	100	5.30	5.80	5.30	5.47	42.70	59.75	66.20	56.22
Average	5.53	5.98	5.98	5.83	25.85	38.13	42.03	35.34	Average	6.20	6.35	6.33	6.29	25.73	35.92	41.10	34.25

Table A5: Low Heterogeneity – DGP3, Case d: High Factor Dependence

	Heterogeneous									*Homogeneous*							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	37.88	35.53	34.74	36.05	46.77	40.69	38.91	42.12	20	45.33	44.47	44.42	44.74	53.33	49.37	48.53	50.41
50	36.58	34.73	34.56	35.29	41.33	37.33	36.58	38.41	50	43.93	44.21	44.29	44.14	49.02	47.13	46.47	47.54
100	36.43	35.55	35.05	35.68	39.85	37.34	36.24	37.81	100	44.80	44.94	44.77	44.84	49.32	47.13	46.23	47.56
Average	36.96	35.27	34.78	35.67	42.65	38.46	37.24	39.45	Average	44.69	44.54	44.49	44.57	50.56	47.88	47.08	48.50
*SW**									*2WFE*								
20	40.86	37.13	35.68	37.89	48.63	41.95	39.74	43.44	20	0.09	-0.05	0.37	0.17	13.47	12.20	11.37	12.34
50	39.49	36.42	35.48	37.13	43.88	38.91	37.46	40.08	50	-0.16	-0.15	0.17	0.16	8.48	7.38	7.35	7.74
100	39.50	37.19	35.99	37.56	42.83	38.92	37.16	39.64	100	-0.01	0.08	-0.18	0.09	5.81	5.49	5.11	5.47
Average	39.95	36.91	35.72	37.53	45.11	39.93	38.12	41.05	Average	0.09	0.10	0.24	0.14	9.25	8.35	7.94	8.52
CCEMG									*CCEP*								
20	-0.04	-0.05	0.20	0.10	12.25	9.87	9.27	10.46	20	0.17	-0.03	0.23	0.15	12.45	10.39	9.73	10.86
50	-0.23	-0.20	0.07	0.17	7.74	6.08	5.78	6.53	50	-0.32	-0.18	0.16	0.22	7.81	6.38	5.97	6.72
100	-0.08	0.14	-0.10	0.11	5.40	4.35	3.95	4.57	100	-0.05	0.08	-0.15	0.09	5.40	4.53	4.06	4.66
Average	0.12	0.13	0.12	0.12	8.46	6.77	6.33	7.19	Average	0.18	0.10	0.18	0.15	8.55	7.10	6.59	7.41
CCEMGX									*CCEPX*								
20	0.16	-0.05	0.21	0.14	12.73	9.89	9.28	10.63	20	0.15	-0.05	0.23	0.14	12.48	10.38	9.72	10.86
50	-0.23	-0.20	0.06	0.16	7.85	6.08	5.78	6.57	50	-0.32	-0.17	0.15	0.22	7.84	6.38	5.97	6.73
100	-0.07	0.15	-0.11	0.11	5.42	4.36	3.95	4.58	100	-0.04	0.08	-0.15	0.09	5.41	4.53	4.06	4.67
Average	0.15	0.13	0.13	0.14	8.67	6.78	6.34	7.26	Average	0.17	0.10	0.18	0.15	8.57	7.10	6.58	7.42
IPCMG									*IPCP*								
20	0.19	-0.01	0.25	0.15	14.09	9.61	9.09	10.93	20	-0.26	-0.35	0.41	0.34	12.71	11.20	10.46	11.46
50	-0.18	-0.15	0.05	0.13	7.57	5.90	5.67	6.38	50	-0.38	-0.24	0.14	0.26	7.92	6.91	6.68	7.17
100	-0.15	0.11	-0.06	0.11	5.06	4.26	3.91	4.41	100	-0.11	0.05	-0.11	0.09	5.48	5.01	4.62	5.04
Average	0.17	0.09	0.12	0.13	8.91	6.59	6.22	7.24	Average	0.25	0.21	0.22	0.23	8.70	7.71	7.26	7.89
PCMGX									*PCPX*								
20	2.71	0.87	0.46	1.34	23.58	13.98	10.87	16.14	20	2.06	0.60	0.41	1.02	20.13	13.59	10.94	14.89
50	1.28	0.31	0.13	0.58	13.89	8.20	6.83	9.64	50	0.79	0.18	0.20	0.39	12.18	8.00	6.90	9.03
100	0.97	0.40	-0.04	0.47	9.89	6.20	4.75	6.95	100	0.64	0.28	-0.11	0.35	8.66	6.01	4.77	6.48
Average	1.65	0.53	0.21	0.80	15.79	9.46	7.48	10.91	Average	1.16	0.36	0.24	0.59	13.66	9.20	7.54	10.13
PCMGX2S									*PCPX2S*								
20	0.54	0.15	0.39	0.36	14.60	9.99	9.21	11.27	20	0.34	0.00	0.27	0.21	12.96	10.33	9.41	10.90
50	0.10	-0.13	0.10	0.11	8.56	6.08	5.74	6.79	50	-0.22	-0.17	0.12	0.17	8.10	6.33	5.90	6.78
100	0.04	0.17	-0.07	0.09	5.70	4.38	3.96	4.68	100	-0.06	0.11	-0.13	0.10	5.49	4.54	4.08	4.70
Average	0.23	0.15	0.18	0.19	9.62	6.82	6.30	7.58	Average	0.21	0.09	0.18	0.16	8.85	7.07	6.46	7.46
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	37.90	49.75	56.80	48.15	9.70	10.65	11.25	10.53	20	52.80	64.25	68.55	61.87	8.80	10.00	10.85	9.88
50	68.15	83.70	89.60	80.48	13.20	17.55	17.90	16.22	50	83.20	92.80	95.40	90.47	12.25	14.25	15.50	14.00
100	87.80	97.95	99.30	95.02	19.50	24.00	30.20	24.57	100	94.25	99.30	99.85	97.80	14.60	20.35	20.85	18.60
Average	64.62	77.13	81.90	74.55	14.13	17.40	19.78	17.11	Average	76.75	85.45	87.93	83.38	11.88	14.87	15.73	14.16
*SW**									*2WFE*								
20	43.95	54.00	59.25	52.40	9.20	10.30	10.95	10.15	20	42.70	56.30	68.85	55.95	13.15	11.25	15.40	13.27
50	77.75	87.45	90.95	85.38	13.95	16.85	17.70	16.17	50	39.85	56.90	68.75	55.17	20.25	24.50	28.20	24.32
100	93.45	98.40	99.40	97.08	19.50	24.55	30.80	24.95	100	40.80	58.00	68.25	55.68	39.15	44.00	48.10	43.75
Average	71.72	79.95	83.20	78.29	14.22	17.23	19.82	17.09	Average	41.12	57.07	68.62	55.60	24.18	26.58	30.57	27.11
CCEMG									*CCEP*								
20	5.55	8.05	7.75	7.12	14.65	16.95	20.30	17.30	20	7.75	7.55	7.90	7.73	13.50	14.95	18.00	15.48
50	6.00	6.10	7.05	6.38	22.95	34.35	39.20	32.17	50	6.25	6.10	6.60	6.32	23.05	33.75	38.30	31.70
100	5.00	6.15	5.70	5.62	45.70	63.35	68.50	59.18	100	5.75	5.90	5.10	5.58	44.50	59.00	66.65	56.72
Average	5.52	6.77	6.83	6.37	27.77	38.22	42.67	36.22	Average	6.58	6.52	6.53	6.54	27.02	35.90	40.98	34.63
CCEMGX									*CCEPX*								
20	4.35	5.70	5.70	5.25	14.15	16.45	20.10	16.90	20	5.95	5.80	6.25	6.00	12.65	15.20	18.30	15.38
50	5.55	5.25	6.05	5.62	22.65	35.00	38.35	32.00	50	5.35	5.45	5.85	5.55	23.65	33.15	37.95	31.58
100	4.40	5.90	5.45	5.25	46.90	63.80	68.00	59.57	100	5.55	5.55	4.70	5.27	44.70	59.50	67.60	57.27
Average	4.77	5.62	5.73	5.37	27.90	38.42	42.15	36.16	Average	5.62	5.60	5.60	5.61	27.00	35.95	41.28	34.74
IPCMG									*IPCP*								
20	5.35	6.90	6.65	6.30	12.80	17.35	19.30	16.48	20	6.90	8.55	9.25	8.23	11.65	14.60	15.50	13.92
50	5.65	5.65	6.00	5.77	25.90	36.75	39.90	34.18	50	6.35	5.90	6.70	6.32	22.20	29.60	32.00	27.93
100	5.35	5.70	5.35	5.47	49.85	64.55	69.20	61.20	100	6.20	5.30	5.40	5.63	43.55	52.85	55.05	50.48
Average	5.45	6.08	6.00	5.84	29.52	39.55	42.80	37.29	Average	6.48	6.58	7.12	6.73	25.80	32.35	34.18	30.78
PCMGX									*PCPX*								
20	6.60	5.85	6.30	6.25	8.20	12.00	15.40	11.87	20	6.10	5.40	6.10	5.87	8.80	11.70	14.60	11.70
50	5.30	4.05	4.95	4.77	13.35	26.55	30.35	23.42	50	5.55	4.00	4.70	4.75	14.65	25.55	31.65	23.95
100	6.85	4.60	3.70	5.05	20.05	38.75	56.55	38.45	100	5.90	5.80	3.95	5.22	23.75	37.45	53.75	38.32
Average	6.25	4.83	4.98	5.36	13.87	25.77	34.10	24.58	Average	5.85	5.07	4.92	5.28	15.73	24.90	33.33	24.66
PCMGX2S									*PCPX2S*								
20	6.05	7.15	6.70	6.63	10.65	16.00	19.60	15.42	20	6.15	7.25	6.95	6.78	11.65	14.25	19.30	15.07
50	6.25	5.65	5.75	5.88	20.25	35.10	38.25	31.20	50	6.40	6.00	6.35	6.25	21.40	33.50	37.55	30.82
100	4.65	6.00	5.20	5.28	42.95	62.05	68.35	57.78	100	4.95	5.45	5.20	5.20	43.10	60.00	66.20	56.43
Average	5.65	6.27	5.88	5.93	24.62	37.72	42.07	34.80	Average	5.83	6.23	6.17	6.08	25.38	35.92	41.02	34.11

Table A6: Low Heterogeneity – DGP4, Case f: Low Spatial Dependence & High Factor Dependence

	Heterogeneous									*Homogeneous*							
T / N	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	35.89	36.26	34.54	35.56	43.58	41.78	38.56	41.31	20	43.41	45.13	43.79	44.11	50.67	50.25	47.72	49.54
50	37.20	35.76	34.71	35.89	42.18	38.34	36.65	39.06	50	44.76	45.22	44.33	44.77	50.18	48.09	46.45	48.24
100	35.92	35.81	35.24	35.66	39.46	37.55	36.46	37.82	100	44.26	45.11	45.12	44.83	48.82	47.21	46.55	47.53
Average	36.33	35.94	34.83	35.70	41.74	39.23	37.22	39.40	Average	44.14	45.15	44.41	44.57	49.89	48.52	46.91	48.44
*SW**									*2WFE*								
20	38.98	37.80	35.45	37.41	45.88	42.94	39.32	42.71	20	-0.21	0.19	-0.16	0.19	12.93	12.24	11.54	12.24
50	40.01	37.44	35.62	37.69	44.51	39.91	37.51	40.65	50	-0.02	-0.26	-0.22	0.17	8.61	7.51	7.35	7.82
100	39.06	37.43	36.19	37.56	42.52	39.11	37.39	39.67	100	-0.07	-0.20	0.09	0.12	5.77	5.31	5.28	5.45
Average	39.35	37.56	35.75	37.55	44.30	40.65	38.08	41.01	Average	0.10	0.22	0.16	0.16	9.11	8.35	8.05	8.50
CCEMG									*CCEP*								
20	-0.34	0.15	-0.18	0.22	11.79	9.78	9.14	10.24	20	-0.52	0.24	-0.16	0.31	12.24	10.47	9.63	10.78
50	0.32	-0.31	0.05	0.23	7.98	6.01	5.75	6.58	50	0.06	-0.22	0.01	0.09	7.80	6.25	5.93	6.66
100	-0.06	-0.18	0.09	0.11	5.32	4.32	4.01	4.55	100	-0.10	-0.25	0.10	0.15	5.39	4.50	4.17	4.69
Average	0.24	0.21	0.11	0.19	8.36	6.71	6.30	7.12	Average	0.22	0.24	0.09	0.18	8.48	7.07	6.58	7.38
CCEMGX									*CCEPX*								
20	-0.24	0.21	-0.18	0.21	12.06	9.88	9.16	10.37	20	-0.51	0.21	-0.16	0.29	12.26	10.47	9.63	10.79
50	0.32	-0.32	0.06	0.23	8.10	6.04	5.77	6.64	50	0.04	-0.23	0.01	0.09	7.83	6.25	5.93	6.67
100	-0.08	-0.19	0.09	0.12	5.35	4.34	4.01	4.57	100	-0.10	-0.25	0.09	0.15	5.40	4.50	4.17	4.69
Average	0.21	0.24	0.11	0.19	8.51	6.75	6.31	7.19	Average	0.22	0.23	0.09	0.18	8.50	7.07	6.58	7.38
IPCMG									*IPCP*								
20	-0.81	0.21	-0.20	0.41	12.64	9.62	8.90	10.39	20	-0.53	-0.11	-0.26	0.30	12.40	11.26	10.54	11.40
50	0.22	-0.30	0.05	0.19	7.78	5.88	5.66	6.44	50	0.00	-0.35	-0.11	0.15	8.10	6.83	6.66	7.20
100	-0.04	-0.17	0.09	0.10	5.03	4.21	3.96	4.40	100	-0.13	-0.26	0.15	0.18	5.51	5.05	4.83	5.13
Average	0.36	0.23	0.11	0.23	8.48	6.57	6.18	7.08	Average	0.22	0.24	0.17	0.21	8.67	7.71	7.34	7.91
PCMGX									*PCPX*								
20	1.75	1.14	0.01	0.97	20.99	14.33	10.76	15.36	20	1.35	0.88	-0.14	0.79	18.61	13.65	10.77	14.34
50	1.16	0.11	0.21	0.50	14.40	8.65	6.78	9.94	50	0.83	0.15	0.13	0.37	12.13	8.27	6.80	9.07
100	0.90	0.27	0.13	0.43	9.61	6.11	4.86	6.86	100	0.80	0.13	0.13	0.35	8.65	5.87	4.87	6.46
Average	1.27	0.51	0.12	0.63	15.00	9.70	7.47	10.72	Average	0.99	0.39	0.14	0.51	13.13	9.26	7.48	9.96
PCMGX2S									*PCPX2S*								
20	-0.15	0.40	-0.15	0.24	13.48	10.10	8.99	10.86	20	-0.35	0.28	-0.23	0.29	12.67	10.35	9.22	10.75
50	0.19	-0.24	0.10	0.18	8.83	6.08	5.71	6.88	50	0.02	-0.24	0.01	0.09	8.17	6.25	5.88	6.77
100	-0.01	-0.16	0.11	0.09	5.66	4.32	3.99	4.66	100	-0.05	-0.24	0.11	0.13	5.52	4.51	4.13	4.72
Average	0.12	0.27	0.12	0.17	9.32	6.84	6.23	7.46	Average	0.14	0.25	0.12	0.17	8.79	7.04	6.41	7.41
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	38.90	51.05	55.30	48.42	9.85	10.45	12.35	10.88	20	51.95	64.20	68.20	61.45	10.60	10.60	11.30	10.83
50	67.10	84.60	90.65	80.78	11.50	16.90	16.85	15.08	50	83.10	93.30	95.60	90.67	12.10	14.00	15.55	13.88
100	87.25	98.55	99.35	95.05	19.10	28.40	30.05	25.85	100	93.70	99.80	99.95	97.82	14.45	21.50	21.60	19.18
Average	64.42	78.07	81.77	74.75	13.48	18.58	19.75	17.27	Average	76.25	85.77	87.92	83.31	12.38	15.37	16.15	14.63
*SW**									*2WFE*								
20	46.35	55.55	58.55	53.48	9.50	10.50	12.05	10.68	20	40.10	58.75	69.55	56.13	11.85	12.10	13.40	12.45
50	77.55	87.50	92.20	85.75	11.50	16.55	16.65	14.90	50	39.60	57.75	68.55	55.30	22.30	25.70	25.95	24.65
100	93.15	99.30	99.50	97.32	17.70	27.50	29.70	24.97	100	38.20	57.65	70.50	55.45	40.75	44.30	49.20	44.75
Average	72.35	80.78	83.42	78.85	12.90	18.18	19.47	16.85	Average	39.30	58.05	69.53	55.63	24.97	27.37	29.52	27.28
CCEMG									*CCEP*								
20	6.60	7.40	7.85	7.28	12.60	15.60	16.45	14.88	20	7.50	7.85	8.00	7.78	12.15	15.85	15.05	14.35
50	6.00	5.90	6.50	6.13	23.30	34.75	40.15	32.73	50	5.60	5.85	6.50	5.98	25.20	32.60	38.00	31.93
100	5.00	6.60	4.85	5.48	46.50	59.85	71.20	59.18	100	5.25	6.10	5.40	5.58	44.30	58.15	66.25	56.23
Average	5.87	6.63	6.40	6.30	27.47	36.73	42.60	35.60	Average	6.12	6.60	6.63	6.45	27.22	35.53	39.77	34.17
CCEMGX									*CCEPX*								
20	4.70	5.90	6.30	5.63	12.60	15.70	16.85	15.05	20	5.40	6.10	6.75	6.08	11.70	15.35	15.30	14.12
50	5.50	5.15	5.95	5.53	22.20	34.90	39.10	32.07	50	5.20	5.25	5.95	5.47	25.25	33.05	37.70	32.00
100	4.70	6.40	4.65	5.25	47.00	58.90	70.75	58.88	100	5.05	5.60	5.15	5.27	43.95	57.40	66.55	55.97
Average	4.97	5.82	5.63	5.47	27.27	36.50	42.23	35.33	Average	5.22	5.65	5.95	5.61	26.97	35.27	39.85	34.03
IPCMG									*IPCP*								
20	5.40	6.10	6.70	6.07	11.50	17.15	17.15	15.27	20	6.85	8.65	9.00	8.17	10.90	14.40	14.10	13.13
50	5.60	5.40	5.70	5.57	24.50	36.25	41.55	34.10	50	6.45	5.75	6.70	6.30	23.25	30.10	31.60	28.32
100	4.95	5.80	4.50	5.08	50.80	63.50	72.75	62.35	100	5.05	6.60	5.85	5.83	45.50	49.55	56.90	50.65
Average	5.32	5.77	5.63	5.57	28.93	38.97	43.82	37.24	Average	6.12	7.00	7.18	6.77	26.55	31.35	34.20	30.70
PCMGX									*PCPX*								
20	5.45	5.85	5.50	5.60	8.75	12.90	14.60	12.08	20	4.85	5.75	5.00	5.20	9.95	12.20	15.25	12.47
50	5.55	5.10	4.95	5.20	12.10	20.00	30.25	20.78	50	5.35	5.00	4.70	5.02	13.70	21.05	31.05	21.93
100	5.10	4.95	4.65	4.90	23.00	39.35	53.35	38.57	100	5.40	5.10	4.85	5.12	26.50	38.35	52.80	39.22
Average	5.37	5.30	5.03	5.23	14.62	24.08	32.73	23.81	Average	5.20	5.28	4.85	5.11	16.72	23.87	33.03	24.54
PCMGX2S									*PCPX2S*								
20	5.90	6.00	6.90	6.27	10.70	16.70	17.05	14.82	20	6.90	6.35	6.85	6.70	11.50	16.80	17.05	15.12
50	5.45	5.85	6.00	5.77	20.20	33.15	40.25	31.20	50	5.20	5.25	6.05	5.50	23.30	33.80	37.85	31.65
100	5.10	6.10	4.70	5.30	41.40	58.80	70.75	56.98	100	5.10	5.55	5.20	5.28	43.55	58.10	67.10	56.25
Average	5.48	5.98	5.87	5.78	24.10	36.22	42.68	34.33	Average	5.73	5.72	6.03	5.83	26.12	36.23	40.67	34.34

Table A7: Low Heterogeneity – DGP4, Case h: High Spatial Dependence & High Factor Dependence

	Heterogeneous									*Homogeneous*							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	35.83	36.35	34.56	35.58	44.57	42.15	38.67	41.80	20	43.23	45.22	43.81	44.09	51.33	50.54	47.80	49.89
50	37.20	35.69	34.73	35.87	42.62	38.41	36.71	39.25	50	44.83	45.18	44.37	44.79	50.48	48.16	46.53	48.39
100	35.89	35.82	35.22	35.64	39.63	37.63	36.47	37.91	100	44.21	45.13	45.09	44.81	48.91	47.28	46.56	47.58
Average	36.31	35.95	34.84	35.70	42.27	39.40	37.28	39.65	Average	44.09	45.17	44.43	44.56	50.24	48.66	46.96	48.62
*SW**									*2WFE*								
20	39.37	38.28	35.63	37.76	47.16	43.64	39.58	43.46	20	-0.18	0.28	-0.13	0.19	13.44	12.37	11.67	12.50
50	40.39	37.68	35.83	37.97	45.24	40.25	37.76	41.08	50	-0.04	-0.30	-0.23	0.19	8.99	7.68	7.42	8.03
100	39.36	37.67	36.34	37.79	43.00	39.41	37.57	39.99	100	-0.10	-0.18	0.08	0.12	6.14	5.42	5.33	5.63
Average	39.71	37.88	35.94	37.84	45.14	41.10	38.30	41.51	Average	0.10	0.25	0.15	0.17	9.53	8.49	8.14	8.72
CCEMG									*CCEP*								
20	-0.32	0.33	-0.21	0.29	14.41	10.56	9.38	11.45	20	-0.54	0.42	-0.20	0.39	13.90	11.06	9.84	11.60
50	0.34	-0.36	0.02	0.24	10.41	6.65	5.96	7.67	50	0.02	-0.25	-0.03	0.10	9.28	6.77	6.12	7.39
100	0.00	-0.16	0.08	0.08	6.81	4.80	4.20	5.27	100	-0.08	-0.22	0.07	0.13	6.37	4.90	4.34	5.20
Average	0.22	0.28	0.10	0.20	10.54	7.34	6.51	8.13	Average	0.21	0.30	0.10	0.20	9.85	7.58	6.77	8.06
CCEMGX									*CCEPX*								
20	-0.07	0.45	-0.19	0.23	15.51	10.85	9.43	11.93	20	-0.61	0.39	-0.19	0.40	13.92	11.01	9.84	11.59
50	0.32	-0.37	0.01	0.23	10.89	6.73	5.99	7.87	50	0.00	-0.27	-0.02	0.10	9.29	6.76	6.12	7.39
100	-0.09	-0.17	0.08	0.11	6.91	4.82	4.21	5.31	100	-0.10	-0.23	0.07	0.13	6.36	4.88	4.33	5.19
Average	0.16	0.33	0.09	0.19	11.10	7.47	6.54	8.37	Average	0.24	0.30	0.09	0.21	9.86	7.55	6.77	8.06
IPCMG									*IPCP*								
20	-0.22	0.34	-0.23	0.26	13.30	10.63	9.65	11.19	20	-1.34	-0.67	-0.55	0.85	13.72	12.05	10.97	12.25
50	0.47	-0.07	0.31	0.28	9.32	6.70	6.26	7.42	50	-0.60	-0.65	-0.49	0.58	9.23	7.40	7.04	7.89
100	0.19	-0.07	0.16	0.14	6.22	4.68	4.22	5.04	100	-0.30	-0.38	0.01	0.23	6.16	5.31	4.91	5.46
Average	0.29	0.16	0.23	0.23	9.61	7.34	6.71	7.89	Average	0.75	0.57	0.35	0.56	9.70	8.25	7.64	8.53
PCMGX									*PCPX*								
20	1.86	1.28	0.05	1.06	24.62	15.53	11.21	17.12	20	1.30	0.98	-0.13	0.81	21.18	14.64	11.18	15.67
50	1.02	0.09	0.19	0.43	16.45	9.25	7.02	10.90	50	0.67	0.10	0.11	0.30	13.52	8.74	7.01	9.76
100	0.86	0.28	0.13	0.42	10.59	6.53	5.04	7.38	100	0.76	0.14	0.13	0.34	9.29	6.23	5.02	6.85
Average	1.25	0.55	0.12	0.64	17.22	10.43	7.75	11.80	Average	0.91	0.41	0.12	0.48	14.66	9.87	7.74	10.76
PCMGX2S									*PCPX2S*								
20	0.09	0.48	-0.18	0.25	16.20	10.89	9.28	12.12	20	-0.21	0.39	-0.21	0.27	14.18	10.88	9.50	11.52
50	0.32	-0.22	0.05	0.20	11.46	6.71	5.89	8.02	50	-0.05	-0.22	0.00	0.09	9.53	6.76	6.07	7.45
100	0.08	-0.15	0.10	0.11	7.30	4.82	4.19	5.44	100	-0.03	-0.22	0.08	0.11	6.57	4.94	4.32	5.28
Average	0.16	0.28	0.11	0.19	11.65	7.47	6.46	8.53	Average	0.10	0.28	0.10	0.16	10.09	7.52	6.63	8.08
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	36.00	49.75	54.90	46.88	9.55	10.70	12.60	10.95	20	50.45	63.10	67.40	60.32	9.90	10.50	11.70	10.70
50	62.90	83.20	90.05	78.72	11.55	15.60	17.20	14.78	50	81.20	92.60	95.45	89.75	11.40	14.20	15.85	13.82
100	84.35	98.05	99.30	93.90	18.30	26.60	28.65	24.52	100	92.70	99.75	99.95	97.47	13.30	21.25	21.85	18.80
Average	61.08	77.00	81.42	73.17	13.13	17.63	19.48	16.75	Average	74.78	85.15	87.60	82.51	11.53	15.32	16.47	14.44
*SW**									*2WFE*								
20	42.50	54.10	58.05	51.55	10.65	11.30	12.30	11.42	20	32.15	51.55	66.10	49.93	11.05	12.40	13.40	12.28
50	74.05	86.85	91.85	84.25	11.95	15.50	17.35	14.93	50	30.75	50.45	61.20	47.47	20.65	25.20	26.00	23.95
100	91.90	99.00	99.55	96.82	16.80	27.65	27.70	24.05	100	31.50	49.10	63.00	47.87	36.95	42.45	48.25	42.55
Average	69.48	79.98	83.15	77.54	13.13	18.15	19.12	16.80	Average	31.47	50.37	63.43	48.42	22.88	26.68	29.22	26.26
CCEMG									*CCEP*								
20	6.45	7.50	7.50	7.15	10.60	14.40	16.40	13.80	20	7.05	7.05	8.10	7.40	10.30	14.80	15.40	13.50
50	5.85	5.90	6.30	6.02	16.45	28.55	36.75	27.25	50	5.60	5.55	6.10	5.75	18.00	29.50	36.40	27.97
100	5.45	6.70	4.70	5.62	30.85	50.80	67.00	49.55	100	4.95	6.30	5.40	5.55	35.75	48.70	61.15	48.53
Average	5.92	6.70	6.17	6.26	19.30	31.25	40.05	30.20	Average	5.87	6.30	6.53	6.23	21.35	31.00	37.65	30.00
CCEMGX									*CCEPX*								
20	2.80	4.90	5.50	4.40	10.10	14.55	16.90	13.85	20	3.55	4.95	6.15	4.88	10.55	14.70	15.55	13.60
50	4.45	4.60	5.40	4.82	14.95	28.95	37.35	27.08	50	3.55	4.35	5.15	4.35	17.75	29.55	37.30	28.20
100	4.05	6.00	4.20	4.75	31.00	50.45	66.20	49.22	100	4.35	5.80	5.35	5.17	35.00	49.10	60.65	48.25
Average	3.77	5.17	5.03	4.66	18.68	31.32	40.15	30.05	Average	3.82	5.03	5.55	4.80	21.10	31.12	37.83	30.02
IPCMG									*IPCP*								
20	5.90	5.90	6.45	6.08	8.95	16.05	15.20	13.40	20	7.00	7.50	7.95	7.48	9.30	13.70	13.25	12.08
50	5.70	5.30	5.45	5.48	20.45	31.00	35.35	28.93	50	6.55	5.85	5.75	6.05	17.50	24.20	26.60	22.77
100	5.05	6.15	4.45	5.22	38.60	54.15	67.55	53.43	100	5.95	6.30	5.55	5.93	35.25	42.85	54.20	44.10
Average	5.55	5.78	5.45	5.59	22.67	33.73	39.37	31.92	Average	6.50	6.55	6.42	6.49	20.68	26.92	31.35	26.32
PCMGX									*PCPX*								
20	5.95	6.10	5.50	5.85	6.70	10.50	13.15	10.12	20	5.05	5.85	5.90	5.60	8.20	11.60	13.60	11.13
50	5.85	5.45	4.65	5.32	9.90	18.65	29.20	19.25	50	5.55	4.95	4.25	4.92	10.15	19.10	30.60	19.95
100	4.95	5.00	4.65	4.87	20.00	36.60	49.80	35.47	100	4.95	5.40	4.65	5.00	22.15	34.70	50.30	35.72
Average	5.58	5.52	4.93	5.34	12.20	21.92	30.72	21.61	Average	5.18	5.40	4.93	5.17	13.50	21.80	31.50	22.27
PCMGX2S									*PCPX2S*								
20	5.50	7.15	6.55	6.40	9.80	15.35	16.55	13.90	20	5.80	6.00	7.10	6.30	9.85	15.60	15.80	13.75
50	5.05	5.60	5.40	5.35	15.45	28.25	37.95	27.22	50	5.55	5.30	5.90	5.58	16.05	29.50	36.25	27.27
100	4.75	6.10	5.05	5.30	29.05	51.40	65.50	48.65	100	4.90	6.00	5.15	5.35	33.05	48.40	63.35	48.27
Average	5.10	6.28	5.67	5.68	18.10	31.67	40.00	29.92	Average	5.42	5.77	6.05	5.74	19.65	31.17	38.47	29.76

Table A8: High Heterogeneity – DGP1: No CSD

	Heterogeneous									*Homogeneous*							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	0.25	-0.18	0.29	0.24	14.36	13.00	12.69	13.35	20	0.15	-0.31	0.40	0.29	15.33	13.66	13.36	14.12
50	0.22	0.28	-0.10	0.20	9.26	8.11	7.88	8.42	50	0.04	0.49	-0.03	0.19	9.64	8.56	8.23	8.81
100	0.06	-0.06	0.22	0.11	6.42	5.77	5.59	5.93	100	-0.03	-0.07	0.25	0.11	6.88	6.20	5.79	6.29
Average	0.18	0.17	0.20	0.18	10.01	8.96	8.72	9.23	Average	0.07	0.29	0.23	0.20	10.62	9.47	9.13	9.74
*SW**									*2WFE*								
20	0.27	-0.19	0.30	0.25	14.02	12.96	12.69	13.23	20	0.46	-0.18	0.30	0.31	18.10	15.01	14.53	15.88
50	0.17	0.31	-0.10	0.19	9.08	8.09	7.88	8.35	50	-0.29	0.23	0.17	0.23	11.11	10.09	9.97	10.39
100	0.02	-0.05	0.23	0.10	6.28	5.77	5.59	5.88	100	-0.10	0.08	0.34	0.17	7.35	7.20	7.08	7.21
Average	0.15	0.18	0.21	0.18	9.79	8.94	8.72	9.15	Average	0.28	0.16	0.27	0.24	12.19	10.77	10.52	11.16
CCEMG									*CCEP*								
20	0.27	-0.14	0.32	0.24	15.29	13.08	12.71	13.69	20	0.02	-0.34	0.42	0.26	15.90	13.73	13.35	14.33
50	0.21	0.31	-0.11	0.21	9.68	8.19	7.89	8.59	50	-0.02	0.54	-0.06	0.20	9.92	8.67	8.20	8.93
100	0.10	-0.06	0.22	0.13	6.72	5.82	5.60	6.05	100	-0.02	-0.10	0.26	0.12	7.17	6.27	5.81	6.42
Average	0.19	0.17	0.22	0.19	10.57	9.03	8.74	9.44	Average	0.02	0.32	0.24	0.20	11.00	9.56	9.12	9.89
CCEMGX									*CCEPX*								
20	0.33	-0.16	0.29	0.26	15.45	13.06	12.73	13.74	20	-0.07	-0.30	0.38	0.25	16.06	13.78	13.39	14.41
50	0.22	0.31	-0.12	0.21	9.73	8.18	7.90	8.60	50	-0.03	0.54	-0.05	0.20	9.98	8.65	8.21	8.95
100	0.09	-0.05	0.22	0.12	6.73	5.82	5.61	6.05	100	-0.05	-0.08	0.26	0.13	7.13	6.27	5.82	6.41
Average	0.21	0.17	0.21	0.20	10.63	9.02	8.74	9.47	Average	0.05	0.31	0.23	0.19	11.05	9.57	9.14	9.92
IPCMG									*IPCP*								
20	0.29	-0.27	0.21	0.26	18.24	13.39	12.76	14.80	20	0.20	-0.39	0.51	0.37	17.40	14.86	14.66	15.64
50	0.18	0.29	-0.09	0.19	9.84	8.24	7.92	8.67	50	0.16	0.40	-0.10	0.22	10.34	8.97	8.46	9.26
100	0.05	-0.05	0.22	0.11	6.81	5.83	5.62	6.08	100	0.03	-0.14	0.27	0.15	7.34	6.32	5.88	6.51
Average	0.17	0.20	0.18	0.18	11.63	9.15	8.76	9.85	Average	0.13	0.31	0.29	0.24	11.69	10.05	9.67	10.47
PCMGX									*PCPX*								
20	0.18	-0.10	0.30	0.20	16.13	13.28	12.75	14.05	20	0.04	-0.33	0.31	0.22	16.64	14.28	13.33	14.75
50	0.21	0.29	-0.06	0.19	9.91	8.33	7.92	8.72	50	0.05	0.52	-0.05	0.20	10.24	8.91	8.30	9.15
100	0.11	-0.03	0.24	0.13	7.07	5.85	5.61	6.18	100	0.06	-0.14	0.28	0.16	7.43	6.32	5.87	6.54
Average	0.17	0.14	0.20	0.17	11.04	9.15	8.76	9.65	Average	0.05	0.33	0.21	0.19	11.44	9.84	9.17	10.15
PCMGX2S									*PCPX2S*								
20	0.18	-0.20	0.27	0.22	16.96	13.41	12.77	14.38	20	0.31	-0.32	0.32	0.32	17.68	14.68	14.13	15.50
50	0.18	0.27	-0.06	0.17	10.23	8.40	7.94	8.86	50	0.03	0.44	-0.11	0.19	10.67	9.13	8.47	9.42
100	0.15	-0.03	0.24	0.14	7.32	5.89	5.63	6.28	100	0.07	-0.19	0.28	0.18	7.77	6.40	5.93	6.70
Average	0.17	0.17	0.19	0.18	11.50	9.23	8.78	9.84	Average	0.14	0.32	0.24	0.23	12.04	10.07	9.51	10.54
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	6.70	5.75	6.25	6.23	10.15	12.75	12.95	11.95	20	6.25	6.25	7.35	6.62	10.80	11.30	11.50	11.20
50	6.60	5.15	6.00	5.92	18.80	23.40	22.75	21.65	50	5.65	5.15	5.70	5.50	19.10	23.20	22.05	21.45
100	4.50	5.75	5.70	5.32	36.70	38.20	43.15	39.35	100	4.70	5.70	5.20	5.20	30.40	35.85	43.05	36.43
Average	5.93	5.55	5.98	5.82	21.88	24.78	26.28	24.32	Average	5.53	5.70	6.08	5.77	20.10	23.45	25.53	23.03
*SW**									*2WFE*								
20	7.90	6.00	6.35	6.75	10.70	12.15	12.70	11.85	20	49.80	59.70	73.00	60.83	9.55	10.95	10.85	10.45
50	6.70	5.20	5.95	5.95	20.35	24.20	22.80	22.45	50	47.55	61.85	75.65	61.68	14.55	16.40	19.25	16.73
100	4.85	5.95	5.65	5.48	36.85	39.00	43.30	39.72	100	44.10	64.65	75.00	61.25	27.60	28.75	30.00	28.78
Average	6.48	5.72	5.98	6.06	22.63	25.12	26.27	24.67	Average	47.15	62.07	74.55	61.26	17.23	18.70	20.03	18.66
CCEMG									*CCEP*								
20	7.30	6.70	7.15	7.05	10.05	12.30	13.40	11.92	20	8.50	7.95	9.05	8.50	9.70	10.60	12.35	10.88
50	6.40	5.60	6.25	6.08	17.90	24.05	21.85	21.27	50	6.20	6.20	6.20	6.20	17.30	22.55	22.50	20.78
100	4.95	5.70	5.60	5.42	34.30	39.00	43.15	38.82	100	5.55	5.85	5.65	5.68	29.15	35.35	43.50	36.00
Average	6.22	6.00	6.33	6.18	20.75	25.12	26.13	24.00	Average	6.75	6.67	6.97	6.79	18.72	22.83	26.12	22.56
CCEMGX									*CCEPX*								
20	6.80	5.75	6.50	6.35	9.60	12.55	12.85	11.67	20	6.70	6.75	7.65	7.03	10.15	10.85	11.10	10.70
50	6.60	5.55	6.00	6.05	17.85	23.20	21.75	20.93	50	6.05	5.10	5.50	5.55	17.55	23.20	22.45	21.07
100	4.90	5.30	5.55	5.25	33.95	38.50	42.90	38.45	100	5.25	5.25	5.45	5.32	28.65	35.45	42.45	35.52
Average	6.10	5.53	6.02	5.88	20.47	24.75	25.83	23.68	Average	6.00	5.70	6.20	5.97	18.78	23.17	25.33	22.43
IPCMG									*IPCP*								
20	6.80	5.95	6.35	6.37	8.50	10.95	13.10	10.85	20	9.65	11.65	13.50	11.60	8.95	10.25	11.40	10.20
50	5.60	5.70	6.00	5.77	17.85	24.10	21.85	21.27	50	8.15	9.10	8.90	8.72	17.10	21.05	22.00	20.05
100	4.95	5.80	5.30	5.35	31.95	38.05	44.10	38.03	100	7.55	7.75	6.75	7.35	28.65	33.00	40.40	34.02
Average	5.78	5.82	5.88	5.83	19.43	24.37	26.35	23.38	Average	8.45	9.50	9.72	9.22	18.23	21.43	24.60	21.42
PCMGX									*PCPX*								
20	7.05	6.05	6.20	6.43	7.80	12.20	13.40	11.13	20	8.25	6.80	7.30	7.45	9.10	10.25	12.00	10.45
50	6.15	5.40	6.15	5.90	17.40	23.25	21.65	20.77	50	6.10	5.70	5.55	5.78	17.75	22.75	22.80	21.10
100	4.40	5.65	5.30	5.12	31.50	35.95	44.05	37.17	100	5.70	5.90	5.00	5.53	27.10	32.55	43.00	34.22
Average	5.87	5.70	5.88	5.82	18.90	23.80	26.37	23.02	Average	6.68	6.13	5.95	6.26	17.98	21.85	25.93	21.92
PCMGX2S									*PCPX2S*								
20	6.90	6.45	6.05	6.47	8.35	11.75	13.25	11.12	20	9.95	9.70	11.65	10.43	8.45	11.00	10.60	10.02
50	6.45	5.10	6.15	5.90	14.70	23.60	22.00	20.10	50	7.75	7.70	8.10	7.85	16.45	20.30	22.00	19.58
100	4.65	5.75	5.25	5.22	28.40	35.10	44.10	35.87	100	6.40	7.70	6.65	6.92	26.60	30.35	40.90	32.62
Average	6.00	5.77	5.82	5.86	17.15	23.48	26.45	22.36	Average	8.03	8.37	8.80	8.40	17.17	20.55	24.50	20.74

Table A9: High Heterogeneity – DGP2, Case a: Low Spatial Dependence

	Heterogeneous									*Homogeneous*							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	-0.02	-0.17	-0.44	0.21	14.07	12.83	12.35	13.08	20	0.15	-0.23	-0.38	0.25	15.04	13.58	12.64	13.75
50	-0.24	0.26	-0.28	0.26	8.85	8.00	7.71	8.19	50	-0.25	0.27	-0.28	0.27	9.55	8.36	8.05	8.65
100	-0.24	-0.12	0.13	0.17	6.35	5.67	5.69	5.90	100	-0.22	-0.19	0.10	0.17	6.75	6.00	5.81	6.18
Average	0.17	0.18	0.28	0.21	9.76	8.83	8.58	9.06	Average	0.21	0.23	0.25	0.23	10.44	9.31	8.83	9.53
*SW**									*2WFE*								
20	0.08	-0.17	-0.43	0.23	13.94	12.82	12.35	13.04	20	0.53	0.16	-0.38	0.36	18.15	15.65	14.02	15.94
50	-0.24	0.26	-0.28	0.26	8.73	8.00	7.71	8.15	50	-0.28	0.34	-0.43	0.35	10.48	10.07	9.95	10.17
100	-0.23	-0.13	0.13	0.16	6.25	5.66	5.68	5.87	100	-0.21	-0.11	0.08	0.14	7.32	7.08	6.61	7.00
Average	0.19	0.18	0.28	0.22	9.64	8.83	8.58	9.02	Average	0.34	0.20	0.30	0.28	11.98	10.93	10.20	11.04
CCEMG									*CCEP*								
20	0.16	-0.15	-0.41	0.24	14.82	12.89	12.37	13.36	20	0.22	-0.18	-0.39	0.27	15.54	13.63	12.65	13.94
50	-0.21	0.23	-0.28	0.24	9.28	8.04	7.72	8.35	50	-0.21	0.30	-0.28	0.26	9.85	8.41	8.07	8.78
100	-0.16	-0.14	0.13	0.15	6.62	5.70	5.70	6.01	100	-0.20	-0.20	0.10	0.17	6.94	6.02	5.83	6.26
Average	0.18	0.17	0.28	0.21	10.24	8.88	8.60	9.24	Average	0.21	0.23	0.26	0.23	10.78	9.35	8.85	9.66
CCEMGX									*CCEPX*								
20	0.30	-0.12	-0.42	0.28	14.89	12.91	12.33	13.38	20	0.33	-0.21	-0.37	0.30	15.60	13.64	12.64	13.96
50	-0.22	0.24	-0.29	0.25	9.26	8.05	7.71	8.34	50	-0.19	0.29	-0.28	0.25	9.90	8.40	8.06	8.79
100	-0.20	-0.14	0.13	0.15	6.71	5.70	5.70	6.04	100	-0.18	-0.19	0.10	0.16	6.98	6.03	5.84	6.28
Average	0.24	0.17	0.28	0.23	10.29	8.89	8.58	9.25	Average	0.23	0.23	0.25	0.24	10.83	9.36	8.84	9.68
IPCMG									*IPCP*								
20	0.02	-0.15	-0.46	0.21	16.23	13.14	12.47	13.95	20	-0.08	-0.36	-0.59	0.34	16.60	14.80	13.92	15.10
50	-0.34	0.27	-0.27	0.30	9.65	8.09	7.74	8.49	50	-0.10	0.30	-0.26	0.22	10.16	8.77	8.43	9.12
100	-0.23	-0.10	0.13	0.16	6.69	5.72	5.69	6.03	100	-0.24	-0.22	0.10	0.19	7.08	6.07	5.92	6.36
Average	0.20	0.18	0.29	0.22	10.85	8.98	8.63	9.49	Average	0.14	0.29	0.32	0.25	11.28	9.88	9.42	10.19
PCMGX									*PCPX*								
20	-0.01	-0.21	-0.44	0.22	15.33	12.94	12.40	13.56	20	0.02	-0.34	-0.35	0.24	15.95	13.74	12.79	14.16
50	-0.23	0.26	-0.26	0.25	9.46	8.10	7.73	8.43	50	-0.13	0.27	-0.30	0.23	10.05	8.53	8.11	8.89
100	-0.31	-0.17	0.13	0.20	6.92	5.77	5.69	6.13	100	-0.35	-0.20	0.12	0.22	7.22	6.09	5.86	6.39
Average	0.18	0.21	0.28	0.22	10.57	8.94	8.60	9.37	Average	0.16	0.27	0.26	0.23	11.07	9.45	8.92	9.81
PCMGX2S									*PCPX2S*								
20	0.06	-0.22	-0.46	0.25	15.87	12.96	12.42	13.75	20	0.05	-0.32	-0.52	0.30	16.79	14.39	13.41	14.86
50	-0.25	0.26	-0.27	0.26	9.93	8.15	7.74	8.61	50	-0.03	0.29	-0.28	0.20	10.43	8.82	8.39	9.21
100	-0.29	-0.15	0.13	0.19	7.18	5.80	5.69	6.22	100	-0.30	-0.21	0.11	0.21	7.52	6.17	5.95	6.54
Average	0.20	0.21	0.29	0.23	10.99	8.97	8.62	9.53	Average	0.12	0.27	0.30	0.23	11.58	9.79	9.25	10.21
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	5.65	6.85	6.95	6.48	10.60	12.35	10.85	11.27	20	6.55	6.95	6.00	6.50	10.05	10.95	11.00	10.67
50	4.95	5.45	4.85	5.08	21.50	23.50	24.80	23.27	50	5.65	5.45	5.50	5.53	18.10	21.85	23.05	21.00
100	5.00	4.70	5.85	5.18	33.90	42.10	42.35	39.45	100	5.30	5.35	5.45	5.37	30.10	35.80	41.55	35.82
Average	5.20	5.67	5.88	5.58	22.00	25.98	26.00	24.66	Average	5.83	5.92	5.65	5.80	19.42	22.87	25.20	22.49
*SW**									*2WFE*								
20	6.75	6.80	6.95	6.83	10.60	12.00	10.55	11.05	20	48.40	62.05	70.20	60.22	9.40	10.35	10.90	10.22
50	5.45	5.25	5.05	5.25	21.45	23.55	24.55	23.18	50	47.45	62.30	75.65	61.80	15.05	16.90	16.10	16.02
100	5.65	4.85	5.85	5.45	34.25	41.60	42.70	39.52	100	44.20	62.85	71.55	59.53	26.30	27.00	32.95	28.75
Average	5.95	5.63	5.95	5.84	22.10	25.72	25.93	24.58	Average	46.68	62.40	72.47	60.52	16.92	18.08	19.98	18.33
CCEMG									*CCEP*								
20	7.05	7.35	7.60	7.33	10.00	12.00	11.00	11.00	20	7.25	8.90	7.40	7.85	8.75	11.25	11.45	10.48
50	6.05	5.90	5.05	5.67	18.35	22.85	24.75	21.98	50	6.85	6.30	5.95	6.37	16.80	20.70	22.85	20.12
100	4.85	4.80	6.05	5.23	32.70	42.30	42.05	39.02	100	5.05	5.70	5.40	5.38	29.90	36.05	41.70	35.88
Average	5.98	6.02	6.23	6.08	20.35	25.72	25.93	24.00	Average	6.38	6.97	6.25	6.53	18.48	22.67	25.33	22.16
CCEMGX									*CCEPX*								
20	6.40	6.45	6.60	6.48	9.30	11.60	11.35	10.75	20	6.20	7.10	5.75	6.35	9.25	11.25	11.85	10.78
50	5.25	5.45	4.85	5.18	19.25	22.70	24.45	22.13	50	6.40	5.25	5.65	5.77	16.70	22.00	23.10	20.60
100	5.50	4.75	5.70	5.32	30.55	42.00	41.40	37.98	100	5.20	5.05	5.05	5.10	28.30	36.90	41.80	35.67
Average	5.72	5.55	5.72	5.66	19.70	25.43	25.73	23.62	Average	5.93	5.80	5.48	5.74	18.08	23.38	25.58	22.35
IPCMG									*IPCP*								
20	5.25	6.80	6.80	6.28	10.80	11.90	10.95	11.22	20	9.50	12.90	11.95	11.45	8.20	10.85	11.40	10.15
50	5.20	5.55	4.85	5.20	17.85	23.70	24.10	21.88	50	8.10	8.45	8.85	8.47	17.75	22.00	22.85	20.87
100	5.20	4.55	5.70	5.15	30.50	42.25	42.55	38.43	100	6.85	6.40	6.90	6.72	26.15	34.30	41.40	33.95
Average	5.22	5.63	5.78	5.54	19.72	25.95	25.87	23.84	Average	8.15	9.25	9.23	8.88	17.37	22.38	25.22	21.66
PCMGX									*PCPX*								
20	6.30	6.85	6.60	6.58	9.15	11.55	10.65	10.45	20	7.10	6.65	6.15	6.63	8.50	10.60	12.05	10.38
50	5.10	5.30	5.05	5.15	18.25	23.30	24.40	21.98	50	5.70	5.20	5.50	5.47	17.55	22.35	22.70	20.87
100	4.90	5.05	5.65	5.20	30.35	39.70	42.60	37.55	100	5.30	5.00	5.05	5.12	27.20	35.10	41.85	34.72
Average	5.43	5.73	5.77	5.64	19.25	24.85	25.88	23.33	Average	6.03	5.62	5.57	5.74	17.75	22.68	25.53	21.99
PCMGX2S									*PCPX2S*								
20	6.25	6.50	7.00	6.58	8.95	12.05	11.25	10.75	20	9.85	9.70	10.20	9.92	8.25	9.95	11.45	9.88
50	5.50	5.30	4.80	5.20	17.20	23.60	24.30	21.70	50	7.95	8.05	7.45	7.82	16.90	22.85	22.60	20.78
100	4.95	4.95	5.70	5.20	28.50	40.40	43.15	37.35	100	6.50	5.80	6.30	6.20	26.85	34.80	41.10	34.25
Average	5.57	5.58	5.83	5.66	18.22	25.35	26.23	23.27	Average	8.10	7.85	7.98	7.98	17.33	22.53	25.05	21.64

Table A10: High Heterogeneity – DGP2, Case *b*: High Spatial Dependence

	Heterogeneous									*Homogeneous*							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	-0.25	-0.20	-0.54	0.33	17.93	13.68	12.85	14.82	20	0.10	-0.25	-0.48	0.27	17.68	14.26	13.09	15.01
50	-0.38	0.25	-0.28	0.30	10.45	8.60	7.95	9.00	50	-0.38	0.25	-0.28	0.30	10.65	8.89	8.26	9.27
100	-0.31	-0.14	0.18	0.21	7.43	6.03	5.84	6.43	100	-0.27	-0.20	0.14	0.20	7.45	6.28	5.96	6.56
Average	0.31	0.20	0.33	0.28	11.94	9.44	8.88	10.09	Average	0.25	0.23	0.30	0.26	11.93	9.81	9.10	10.28
*SW**									*2WFE*								
20	-0.06	-0.19	-0.52	0.25	17.19	13.65	12.85	14.56	20	0.59	0.17	-0.42	0.39	19.02	15.82	14.08	16.31
50	-0.42	0.26	-0.29	0.32	10.10	8.56	7.94	8.87	50	-0.31	0.36	-0.43	0.37	10.96	10.28	10.04	10.43
100	-0.24	-0.15	0.18	0.19	7.16	6.02	5.83	6.34	100	-0.23	-0.13	0.10	0.16	7.62	7.18	6.69	7.17
Average	0.24	0.20	0.33	0.26	11.48	9.41	8.87	9.92	Average	0.38	0.22	0.32	0.31	12.54	11.09	10.27	11.30
CCEMG									*CCEP*								
20	0.18	-0.17	-0.45	0.26	17.34	13.34	12.60	14.43	20	0.34	-0.23	-0.41	0.33	17.36	13.99	12.85	14.73
50	-0.29	0.21	-0.31	0.27	10.95	8.57	7.92	9.15	50	-0.29	0.28	-0.29	0.29	10.95	8.87	8.25	9.36
100	-0.17	-0.17	0.16	0.17	7.89	6.05	5.86	6.60	100	-0.22	-0.22	0.12	0.19	7.72	6.29	5.98	6.67
Average	0.21	0.18	0.31	0.23	12.06	9.32	8.79	10.06	Average	0.28	0.25	0.28	0.27	12.01	9.72	9.03	10.25
CCEMGX									*CCEPX*								
20	0.26	-0.12	-0.46	0.28	18.51	13.46	12.60	14.86	20	0.43	-0.20	-0.42	0.35	17.37	14.01	12.83	14.74
50	-0.36	0.26	-0.31	0.31	11.05	8.61	7.91	9.19	50	-0.28	0.30	-0.29	0.29	10.98	8.86	8.24	9.36
100	-0.23	-0.16	0.16	0.18	8.04	6.09	5.87	6.66	100	-0.18	-0.21	0.13	0.17	7.73	6.31	5.99	6.68
Average	0.28	0.18	0.31	0.26	12.53	9.39	8.79	10.24	Average	0.30	0.24	0.28	0.27	12.03	9.73	9.02	10.26
IPCMG									*IPCP*								
20	-0.24	-0.18	-0.44	0.29	15.95	13.09	12.47	13.84	20	0.08	-0.28	-0.42	0.26	16.35	13.82	12.79	14.32
50	-0.29	0.22	-0.32	0.27	10.29	8.36	7.91	8.85	50	-0.27	0.29	-0.34	0.30	10.45	8.72	8.24	9.14
100	-0.27	-0.19	0.17	0.21	7.45	5.99	5.82	6.42	100	-0.12	-0.24	0.12	0.16	7.54	6.28	5.96	6.59
Average	0.27	0.19	0.31	0.26	11.23	9.15	8.73	9.70	Average	0.16	0.27	0.29	0.24	11.45	9.61	9.00	10.02
PCMGX									*PCPX*								
20	-0.46	-0.24	-0.54	0.41	21.15	14.09	13.06	16.10	20	-0.10	-0.36	-0.43	0.29	19.92	14.60	13.36	15.96
50	-0.35	0.28	-0.26	0.29	11.75	8.83	8.01	9.53	50	-0.21	0.28	-0.29	0.26	11.43	9.17	8.34	9.64
100	-0.39	-0.22	0.17	0.26	8.61	6.28	5.88	6.92	100	-0.40	-0.22	0.17	0.26	8.24	6.46	6.03	6.91
Average	0.40	0.25	0.32	0.32	13.84	9.74	8.98	10.85	Average	0.23	0.29	0.30	0.27	13.20	10.08	9.24	10.84
PCMGX2S									*PCPX2S*								
20	-0.07	-0.24	-0.47	0.26	18.23	13.32	12.56	14.70	20	-0.09	-0.41	-0.39	0.30	17.53	14.06	12.92	14.83
50	-0.31	0.25	-0.30	0.29	11.45	8.57	7.93	9.32	50	-0.14	0.30	-0.34	0.26	11.12	8.94	8.30	9.45
100	-0.38	-0.25	0.16	0.26	8.53	6.23	5.84	6.87	100	-0.24	-0.27	0.15	0.22	8.22	6.44	6.01	6.89
Average	0.25	0.25	0.31	0.27	12.74	9.37	8.78	10.30	Average	0.16	0.32	0.29	0.26	12.29	9.81	9.08	10.39

	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	5.60	6.90	6.30	6.27	8.60	11.20	11.00	10.27	20	6.60	6.75	6.35	6.57	8.10	11.10	10.90	10.03
50	4.70	5.40	4.80	4.97	16.55	22.25	23.50	20.77	50	5.65	5.05	5.40	5.37	15.55	21.85	21.15	19.52
100	4.60	4.60	5.55	4.92	26.75	38.15	41.60	35.50	100	4.75	5.30	5.15	5.07	26.40	33.65	39.80	33.28
Average	4.97	5.63	5.55	5.38	17.30	23.87	25.37	22.18	Average	5.67	5.70	5.63	5.67	16.68	22.20	23.95	20.94
*SW**									*2WFE*								
20	5.30	7.55	6.35	6.40	8.35	12.10	10.50	10.32	20	39.50	56.20	64.80	53.50	8.85	10.80	10.75	10.13
50	6.20	5.35	4.95	5.50	16.35	21.45	23.50	20.43	50	36.90	53.15	69.50	53.18	14.10	17.15	16.20	15.82
100	5.20	4.75	5.50	5.15	28.75	37.50	41.40	35.88	100	34.85	53.25	64.20	50.77	26.00	27.35	32.80	28.72
Average	5.57	5.88	5.60	5.68	17.82	23.68	25.13	22.21	Average	37.08	54.20	66.17	52.48	16.32	18.43	19.92	18.22
CCEMG									*CCEP*								
20	7.15	8.20	7.60	7.65	9.00	11.55	10.25	10.27	20	8.10	8.75	7.25	8.03	9.10	11.10	10.70	10.30
50	5.85	6.05	5.20	5.70	16.00	20.20	24.10	20.10	50	6.45	6.00	6.05	6.17	14.10	19.85	21.10	18.35
100	5.45	5.20	5.95	5.53	23.10	36.30	40.45	33.28	100	5.55	5.25	5.10	5.30	23.55	34.05	41.05	32.88
Average	6.15	6.48	6.25	6.29	16.03	22.68	24.93	21.22	Average	6.70	6.67	6.13	6.50	15.58	21.67	24.28	20.51
CCEMGX									*CCEPX*								
20	4.00	5.80	5.80	5.20	8.15	11.85	11.35	10.45	20	4.30	6.10	5.75	5.38	8.80	10.40	10.80	10.00
50	4.55	5.25	4.75	4.85	14.65	21.45	23.10	19.73	50	6.15	4.85	5.40	5.47	13.40	21.35	21.25	18.67
100	5.00	4.80	5.35	5.05	22.65	37.65	41.25	33.85	100	5.00	4.70	4.90	4.87	24.15	34.25	40.35	32.92
Average	4.52	5.28	5.30	5.03	15.15	23.65	25.23	21.34	Average	5.15	5.22	5.35	5.24	15.45	22.00	24.13	20.53
IPCMG									*IPCP*								
20	6.10	6.80	6.45	6.45	8.80	11.65	10.90	10.45	20	6.90	6.90	6.85	6.88	9.40	12.20	11.10	10.90
50	5.95	5.50	4.70	5.38	15.20	21.70	24.60	20.50	50	6.35	5.70	5.70	5.92	14.70	20.55	21.45	18.90
100	4.90	4.95	5.45	5.10	26.60	38.00	42.00	35.53	100	5.60	5.95	5.20	5.58	25.60	31.85	40.70	32.72
Average	5.65	5.75	5.53	5.64	16.87	23.78	25.83	22.16	Average	6.28	6.18	5.92	6.13	16.57	21.53	24.42	20.84
PCMGX									*PCPX*								
20	5.95	6.70	6.25	6.30	7.35	10.55	11.30	9.73	20	6.35	7.05	5.90	6.43	7.85	10.20	11.00	9.68
50	4.80	5.20	4.55	4.85	14.95	22.15	23.30	20.13	50	6.00	5.05	5.55	5.53	13.50	20.25	20.45	18.07
100	5.05	5.55	5.50	5.37	20.85	32.85	41.40	31.70	100	5.65	4.65	4.60	4.97	22.15	33.50	41.80	32.48
Average	5.27	5.82	5.43	5.51	14.38	21.85	25.33	20.52	Average	6.00	5.58	5.35	5.64	14.50	21.32	24.42	20.08
PCMGX2S									*PCPX2S*								
20	6.05	6.80	6.55	6.47	9.10	11.10	11.30	10.50	20	7.45	7.25	6.50	7.07	7.50	10.15	11.80	9.82
50	5.65	5.50	4.50	5.22	13.80	21.05	24.00	19.62	50	6.00	5.85	5.05	5.63	15.30	19.00	23.05	19.12
100	5.00	5.45	5.65	5.37	20.90	34.40	41.15	32.15	100	5.45	5.20	5.10	5.25	23.20	32.65	40.15	32.00
Average	5.57	5.92	5.57	5.68	14.60	22.18	25.48	20.76	Average	6.30	6.10	5.55	5.98	15.33	20.60	25.00	20.31

Table A11: High Heterogeneity – DGP3, Case *c*: Low Factor Dependence

	Heterogeneous									*Homogeneous*							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	18.81	17.62	17.61	18.01	26.60	23.54	23.02	24.39	20	22.72	22.10	22.74	22.52	30.98	28.48	28.63	29.36
50	18.13	17.26	17.34	17.58	22.06	20.00	19.84	20.63	50	21.92	22.03	22.27	22.07	26.35	25.12	25.13	25.53
100	18.03	17.87	17.46	17.79	20.60	19.53	18.76	19.63	100	22.33	22.54	22.31	22.39	25.65	24.58	23.92	24.72
Average	18.32	17.59	17.47	17.79	23.09	21.02	20.54	21.55	Average	22.32	22.22	22.44	22.33	27.66	26.06	25.89	26.54
*SW**									*2WFE*								
20	19.80	18.02	17.82	18.55	27.04	23.80	23.18	24.68	20	0.20	-0.22	0.60	0.34	17.30	16.20	15.06	16.19
50	18.94	17.70	17.54	18.06	22.66	20.37	20.01	21.01	50	-0.18	-0.11	0.24	0.17	10.88	9.71	9.80	10.13
100	18.98	18.28	17.68	18.31	21.48	19.90	18.97	20.12	100	-0.04	0.14	-0.24	0.14	7.50	7.27	6.77	7.18
Average	19.24	18.00	17.68	18.31	23.73	21.36	20.72	21.94	Average	0.14	0.16	0.36	0.22	11.89	11.06	10.54	11.16
CCEMG									*CCEP*								
20	-0.03	-0.12	0.35	0.16	14.75	13.01	12.69	13.48	20	0.24	-0.14	0.38	0.25	15.98	13.81	13.29	14.36
50	-0.31	-0.22	0.09	0.21	9.42	8.15	7.95	8.51	50	-0.37	-0.19	0.21	0.26	10.08	8.63	8.23	8.98
100	-0.17	0.19	-0.13	0.16	6.61	5.86	5.46	5.97	100	-0.11	0.11	-0.19	0.14	6.99	6.18	5.63	6.27
Average	0.17	0.17	0.19	0.18	10.26	9.01	8.70	9.32	Average	0.24	0.15	0.26	0.22	11.02	9.54	9.05	9.87
CCEMGX									*CCEPX*								
20	0.09	-0.15	0.35	0.20	14.95	12.98	12.69	13.54	20	0.19	-0.18	0.37	0.25	15.99	13.80	13.29	14.36
50	-0.30	-0.21	0.08	0.20	9.49	8.15	7.95	8.53	50	-0.38	-0.18	0.21	0.26	10.11	8.62	8.23	8.99
100	-0.15	0.19	-0.13	0.16	6.62	5.87	5.45	5.98	100	-0.10	0.11	-0.20	0.14	6.99	6.18	5.63	6.27
Average	0.18	0.19	0.19	0.18	10.35	9.00	8.70	9.35	Average	0.22	0.16	0.26	0.21	11.03	9.53	9.05	9.87
IPCMG									*IPCP*								
20	0.35	-0.03	0.39	0.26	16.13	13.03	12.70	13.96	20	-1.36	-1.33	-0.59	1.09	17.07	15.29	14.26	15.54
50	-0.06	-0.13	0.08	0.09	9.36	8.03	7.90	8.43	50	-1.54	-1.48	-1.02	1.35	10.54	9.56	9.11	9.73
100	-0.18	0.17	-0.09	0.15	6.39	5.81	5.43	5.88	100	-1.34	-1.20	-1.57	1.37	7.48	6.94	6.58	7.00
Average	0.20	0.11	0.19	0.16	10.63	8.96	8.68	9.42	Average	1.41	1.34	1.06	1.27	11.70	10.60	9.98	10.76
PCMGX									*PCPX*								
20	1.35	0.30	0.49	0.71	18.38	13.95	13.05	15.12	20	1.12	0.18	0.47	0.59	18.06	14.47	13.34	15.29
50	0.50	0.04	0.14	0.23	11.15	8.58	8.15	9.29	50	0.16	0.00	0.23	0.13	11.09	8.90	8.37	9.45
100	0.37	0.32	-0.09	0.26	7.77	6.31	5.62	6.57	100	0.20	0.22	-0.16	0.20	7.75	6.52	5.77	6.68
Average	0.74	0.22	0.24	0.40	12.43	9.61	8.94	10.33	Average	0.50	0.13	0.29	0.31	12.30	9.97	9.16	10.47
PCMGX2S									*PCPX2S*								
20	0.56	-0.01	0.46	0.35	16.04	13.08	12.70	13.94	20	0.11	-0.16	0.35	0.21	16.69	14.00	13.13	14.61
50	0.01	-0.17	0.11	0.10	9.98	8.15	7.95	8.69	50	-0.42	-0.17	0.16	0.25	10.43	8.69	8.20	9.11
100	-0.05	0.22	-0.10	0.13	6.76	5.89	5.47	6.04	100	-0.14	0.12	-0.19	0.15	7.06	6.22	5.67	6.31
Average	0.21	0.14	0.23	0.19	10.93	9.04	8.70	9.56	Average	0.22	0.15	0.23	0.20	11.39	9.64	9.00	10.01
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	22.70	23.95	26.00	24.22	12.80	13.10	16.35	14.08	20	26.60	26.80	31.65	28.35	11.25	12.65	13.90	12.60
50	41.15	46.20	48.50	45.28	19.25	23.20	23.75	22.07	50	46.80	53.40	55.65	51.95	17.90	20.30	22.60	20.27
100	62.20	71.05	76.35	69.87	28.35	36.45	40.20	35.00	100	67.70	77.10	81.30	75.37	23.95	24.85	29.85	26.22
Average	42.02	47.07	50.28	46.46	20.13	24.25	26.77	23.72	Average	47.03	52.43	56.20	51.89	17.70	19.27	22.12	19.69
*SW**									*2WFE*								
20	24.85	24.80	26.70	25.45	12.95	14.05	16.75	14.58	20	49.50	63.75	74.25	62.50	9.40	9.40	11.95	10.25
50	45.25	48.35	49.60	47.73	19.05	22.90	23.80	21.92	50	47.20	62.90	73.70	61.27	13.90	17.35	18.35	16.53
100	66.40	72.85	77.25	72.17	28.20	36.75	40.25	35.07	100	49.30	65.20	73.40	62.63	26.90	28.35	29.95	28.40
Average	45.50	48.67	51.18	48.45	20.07	24.57	26.93	23.86	Average	48.67	63.95	73.78	62.13	16.73	18.37	20.08	18.39
CCEMG									*CCEP*								
20	6.70	7.90	8.10	7.57	11.50	11.50	13.15	12.05	20	8.25	7.30	8.35	7.97	9.95	11.25	12.60	11.27
50	5.75	6.20	6.85	6.27	16.75	22.05	23.00	20.60	50	6.55	6.00	6.60	6.38	15.15	20.75	22.70	19.53
100	4.95	5.80	5.60	5.45	33.90	41.10	42.05	39.02	100	5.45	5.60	5.30	5.45	29.50	37.35	39.05	35.30
Average	5.80	6.63	6.85	6.43	20.72	24.88	26.07	23.89	Average	6.75	6.30	6.75	6.60	18.20	23.12	24.78	22.03
CCEMGX									*CCEPX*								
20	5.35	6.60	6.45	6.13	11.40	11.50	13.15	12.02	20	6.55	5.95	7.30	6.60	9.90	11.20	12.00	11.03
50	5.85	5.70	6.25	5.93	16.90	22.25	22.70	20.62	50	6.10	5.60	6.05	5.92	15.35	21.15	22.25	19.58
100	4.75	5.65	5.30	5.23	33.35	40.95	41.70	38.67	100	5.35	5.35	5.15	5.28	29.15	36.80	39.30	35.08
Average	5.32	5.98	6.00	5.77	20.55	24.90	25.85	23.77	Average	6.00	5.63	6.17	5.93	18.13	23.05	24.52	21.90
IPCMG									*IPCP*								
20	5.60	6.50	6.70	6.27	11.00	11.55	12.55	11.70	20	9.20	10.85	11.45	10.50	7.95	9.50	10.95	9.47
50	5.65	5.70	5.90	5.75	16.95	21.30	23.05	20.43	50	7.65	7.75	8.70	8.03	11.85	14.80	16.65	14.43
100	5.00	5.85	5.55	5.47	34.55	41.20	41.85	39.20	100	7.55	7.35	7.40	7.43	22.40	24.50	24.35	23.75
Average	5.42	6.02	6.05	5.83	20.83	24.68	25.82	23.78	Average	8.13	8.65	9.18	8.66	14.07	16.27	17.32	15.88
PCMGX									*PCPX*								
20	6.05	6.85	6.70	6.53	10.50	10.70	12.70	11.30	20	6.95	6.40	6.45	6.60	9.80	10.35	11.55	10.57
50	5.55	5.35	5.55	5.48	14.85	20.70	22.40	19.32	50	5.35	5.65	5.50	5.50	15.70	19.40	22.65	19.25
100	5.35	5.55	4.75	5.22	25.50	36.25	41.05	34.27	100	5.15	5.75	4.75	5.22	26.05	31.55	38.95	32.18
Average	5.65	5.92	5.67	5.74	16.95	22.55	25.38	21.63	Average	5.82	5.93	5.57	5.77	17.18	20.43	24.38	20.67
PCMGX2S									*PCPX2S*								
20	5.90	6.80	7.00	6.57	9.35	11.15	12.95	11.15	20	7.50	8.30	7.70	7.83	9.45	10.15	11.25	10.28
50	5.60	5.45	6.25	5.77	16.15	22.45	23.35	20.65	50	6.50	6.25	6.50	6.42	13.95	21.10	22.35	19.13
100	4.90	5.75	5.50	5.38	31.95	40.35	41.20	37.83	100	4.95	6.20	5.00	5.38	30.70	36.05	40.50	35.75
Average	5.47	6.00	6.25	5.91	19.15	24.65	25.83	23.21	Average	6.32	6.92	6.40	6.54	18.03	22.43	24.70	21.72

Table A12: High Heterogeneity – DGP3, Case *d*: High Factor Dependence

	Heterogeneous									*Homogeneous*							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	37.89	35.44	34.85	36.06	47.61	41.54	40.00	43.05	20	45.38	44.39	44.68	44.81	54.57	50.43	49.93	51.64
50	36.48	34.71	34.58	35.26	41.59	37.68	37.01	38.76	50	43.90	44.20	44.34	44.14	49.51	47.55	47.01	48.02
100	36.35	35.60	35.01	35.65	39.97	37.58	36.40	37.99	100	44.76	44.98	44.74	44.82	49.58	47.42	46.44	47.81
Average	36.90	35.25	34.82	35.66	43.06	38.94	37.80	39.93	Average	44.68	44.52	44.58	44.59	51.22	48.47	47.79	49.16
*SW**									*2WFE*								
20	40.58	36.75	35.60	37.64	49.29	42.55	40.65	44.16	20	0.18	-0.18	0.58	0.31	17.81	16.49	15.39	16.57
50	39.01	36.11	35.31	36.81	43.82	38.99	37.70	40.17	50	-0.20	-0.14	0.24	0.19	11.18	9.92	9.99	10.36
100	39.06	36.94	35.76	37.25	42.62	38.88	37.13	39.55	100	-0.03	0.13	-0.25	0.14	7.70	7.41	6.91	7.34
Average	39.55	36.60	35.55	37.23	45.24	40.14	38.49	41.29	Average	0.14	0.15	0.36	0.21	12.23	11.28	10.77	11.42
CCEMG									*CCEP*								
20	-0.03	-0.14	0.32	0.16	14.95	13.14	12.77	13.62	20	0.24	-0.15	0.36	0.25	16.15	13.95	13.39	14.50
50	-0.34	-0.22	0.09	0.22	9.47	8.19	7.98	8.55	50	-0.40	-0.20	0.21	0.27	10.12	8.66	8.27	9.02
100	-0.16	0.19	-0.13	0.16	6.64	5.87	5.46	5.99	100	-0.10	0.11	-0.20	0.14	7.00	6.18	5.64	6.27
Average	0.18	0.18	0.18	0.18	10.35	9.07	8.74	9.38	Average	0.25	0.15	0.26	0.22	11.09	9.60	9.10	9.93
CCEMGX									*CCEPX*								
20	0.17	-0.15	0.33	0.22	15.36	13.14	12.77	13.76	20	0.20	-0.17	0.35	0.24	16.17	13.94	13.39	14.50
50	-0.33	-0.22	0.08	0.21	9.56	8.18	7.98	8.57	50	-0.41	-0.19	0.21	0.27	10.15	8.66	8.26	9.02
100	-0.15	0.19	-0.14	0.16	6.65	5.88	5.46	6.00	100	-0.10	0.11	-0.21	0.14	7.01	6.19	5.63	6.28
Average	0.22	0.19	0.18	0.20	10.53	9.07	8.74	9.44	Average	0.23	0.16	0.26	0.22	11.11	9.59	9.10	9.93
IPCMG									*IPCP*								
20	0.20	-0.11	0.37	0.23	16.53	12.93	12.64	14.03	20	-0.70	-0.68	0.27	0.55	16.98	15.37	14.45	15.60
50	-0.28	-0.17	0.07	0.17	9.39	8.04	7.90	8.44	50	-0.78	-0.56	0.01	0.45	10.57	9.49	9.22	9.76
100	-0.24	0.15	-0.10	0.16	6.35	5.81	5.43	5.86	100	-0.47	-0.12	-0.28	0.29	7.36	6.91	6.42	6.90
Average	0.24	0.14	0.18	0.19	10.76	8.93	8.65	9.45	Average	0.65	0.45	0.19	0.43	11.64	10.59	10.03	10.75
PCMGX									*PCPX*								
20	2.71	0.77	0.58	1.35	25.23	16.47	14.00	18.56	20	2.09	0.50	0.53	1.04	22.64	16.47	14.20	17.77
50	1.18	0.29	0.16	0.54	14.90	9.82	8.74	11.15	50	0.67	0.17	0.25	0.37	13.73	9.86	8.92	10.84
100	0.89	0.44	-0.07	0.47	10.59	7.34	6.05	8.00	100	0.59	0.31	-0.16	0.35	9.72	7.33	6.16	7.74
Average	1.59	0.50	0.27	0.79	16.91	11.21	9.60	12.57	Average	1.12	0.33	0.31	0.59	15.36	11.22	9.76	12.11
PCMGX2S									*PCPX2S*								
20	0.55	0.05	0.50	0.37	16.98	13.22	12.73	14.31	20	0.36	-0.09	0.36	0.27	16.69	13.99	13.11	14.60
50	-0.01	-0.15	0.12	0.09	10.18	8.18	7.95	8.77	50	-0.38	-0.18	0.17	0.24	10.44	8.66	8.20	9.10
100	-0.04	0.22	-0.10	0.12	6.85	5.90	5.47	6.07	100	-0.14	0.13	-0.19	0.15	7.05	6.19	5.67	6.30
Average	0.20	0.14	0.24	0.19	11.34	9.10	8.71	9.72	Average	0.29	0.13	0.24	0.22	11.40	9.62	8.99	10.00

	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	34.70	41.90	48.55	41.72	9.50	10.20	11.75	10.48	20	46.20	53.95	59.65	53.27	9.00	9.55	10.05	9.53
50	63.55	76.30	80.90	73.58	13.25	15.05	16.20	14.83	50	74.95	85.60	89.05	83.20	11.25	12.95	14.90	13.03
100	84.00	95.30	97.20	92.17	17.75	21.45	24.85	21.35	100	90.05	97.60	99.00	95.55	14.80	16.85	19.00	16.88
Average	60.75	71.17	75.55	69.16	13.50	15.57	17.60	15.56	Average	70.40	79.05	82.57	77.34	11.68	13.12	14.65	13.15
*SW**									*2WFE*								
20	40.45	45.30	50.15	45.30	8.65	10.00	11.45	10.03	20	48.60	61.70	73.40	61.23	9.45	8.70	10.70	9.62
50	71.15	80.10	82.95	78.07	12.85	15.40	16.15	14.80	50	46.45	61.75	73.10	60.43	14.20	16.10	18.25	16.18
100	89.90	96.60	97.70	94.73	17.65	21.60	25.55	21.60	100	47.15	64.85	72.15	61.38	25.65	26.45	29.40	27.17
Average	67.17	74.00	76.93	72.70	13.05	15.67	17.72	15.48	Average	47.40	62.77	72.88	61.02	16.43	17.08	19.45	17.66
CCEMG									*CCEP*								
20	5.85	8.00	7.95	7.27	11.80	11.95	13.00	12.25	20	8.20	7.35	8.35	7.97	9.75	11.35	12.20	11.10
50	5.95	6.30	6.80	6.35	17.10	21.85	22.90	20.62	50	6.30	6.00	6.65	6.32	15.10	20.65	22.85	19.53
100	5.05	5.90	5.65	5.53	32.85	41.15	41.45	38.48	100	5.70	5.35	5.35	5.47	28.55	36.95	39.40	34.97
Average	5.62	6.73	6.80	6.38	20.58	24.98	25.78	23.78	Average	6.73	6.23	6.78	6.58	17.80	22.98	24.82	21.87
CCEMGX									*CCEPX*								
20	5.20	6.15	6.20	5.85	11.15	11.85	13.30	12.10	20	6.35	5.80	7.05	6.40	9.90	11.05	11.75	10.90
50	5.60	5.45	6.30	5.78	17.05	21.95	22.70	20.57	50	5.85	5.60	6.10	5.85	15.35	20.85	22.80	19.67
100	4.75	5.70	5.25	5.23	33.00	40.80	41.45	38.42	100	5.35	5.25	5.20	5.27	29.15	36.60	39.35	35.03
Average	5.18	5.77	5.92	5.62	20.40	24.87	25.82	23.69	Average	5.85	5.55	6.12	5.84	18.13	22.83	24.63	21.87
IPCMG									*IPCP*								
20	5.80	6.85	6.50	6.38	10.20	11.40	12.80	11.47	20	8.55	10.00	10.30	9.62	8.75	10.60	11.00	10.12
50	5.65	5.45	5.95	5.68	17.00	20.70	23.20	20.30	50	7.45	6.80	7.95	7.40	12.35	17.30	17.50	15.72
100	5.10	5.75	5.55	5.47	33.95	41.15	41.85	38.98	100	6.75	6.55	6.05	6.45	25.75	31.00	31.40	29.38
Average	5.52	6.02	6.00	5.84	20.38	24.42	25.95	23.58	Average	7.58	7.78	8.10	7.82	15.62	19.63	19.97	18.41
PCMGX									*PCPX*								
20	6.35	5.75	6.25	6.12	8.15	9.75	11.60	9.83	20	6.35	5.45	6.70	6.17	8.15	9.80	10.45	9.47
50	5.55	4.30	5.15	5.00	10.95	19.15	20.50	16.87	50	5.30	4.70	5.10	5.03	12.90	18.45	21.25	17.53
100	6.15	5.15	3.95	5.08	17.95	28.25	37.80	28.00	100	5.65	5.90	4.40	5.32	18.05	26.10	34.30	26.15
Average	6.02	5.07	5.12	5.40	12.35	19.05	23.30	18.23	Average	5.77	5.35	5.40	5.51	13.03	18.12	22.00	17.72
PCMGX2S									*PCPX2S*								
20	6.05	7.30	7.20	6.85	9.05	10.95	13.40	11.13	20	7.00	8.35	7.30	7.55	8.60	10.05	11.40	10.02
50	6.30	5.50	5.95	5.92	14.70	22.15	23.05	19.97	50	6.30	6.00	6.50	6.27	14.25	20.55	23.00	19.27
100	4.80	5.90	5.40	5.37	31.55	39.80	41.75	37.70	100	4.85	6.05	5.20	5.37	29.45	36.95	39.20	35.20
Average	5.72	6.23	6.18	6.04	18.43	24.30	26.07	22.93	Average	6.05	6.80	6.33	6.39	17.43	22.52	24.53	21.49

Table A13: High Heterogeneity – DGP4, Case f: Low Spatial Dependence & High Factor Dependence

T / N	*Heterogeneous*									*Homogeneous*							
	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	35.74	36.25	34.43	35.47	44.22	42.67	39.32	42.07	20	43.18	45.13	43.67	44.00	51.59	51.37	48.73	50.56
50	37.25	35.67	34.72	35.88	42.61	38.59	37.05	39.42	50	44.76	45.18	44.30	44.74	50.68	48.48	46.88	48.68
100	35.87	35.75	35.28	35.63	39.61	37.68	36.70	38.00	100	44.24	45.02	45.17	44.81	49.06	47.33	46.85	47.75
Average	36.29	35.89	34.81	35.66	42.15	39.65	37.69	39.83	Average	44.06	45.11	44.38	44.52	50.44	49.06	47.49	49.00
*SW**									*2WFE*								
20	38.54	37.50	35.14	37.06	46.25	43.59	39.91	43.25	20	-0.33	0.23	-0.25	0.27	17.13	16.49	15.51	16.38
50	39.71	37.08	35.42	37.40	44.64	39.90	37.71	40.75	50	-0.03	-0.32	-0.29	0.22	11.30	10.02	9.89	10.40
100	38.66	37.07	36.04	37.26	42.33	38.95	37.45	39.58	100	-0.07	-0.28	0.14	0.16	7.61	7.13	7.16	7.30
Average	38.97	37.22	35.53	37.24	44.41	40.81	38.36	41.19	Average	0.15	0.28	0.23	0.22	12.02	11.21	10.85	11.36
CCEMG									*CCEP*								
20	-0.49	0.14	-0.29	0.30	14.37	13.07	12.52	13.32	20	-0.69	0.28	-0.26	0.41	15.74	14.13	13.19	14.36
50	0.37	-0.40	0.05	0.27	9.69	8.05	7.93	8.56	50	0.07	-0.27	0.00	0.12	10.08	8.47	8.21	8.92
100	-0.11	-0.25	0.13	0.16	6.53	5.81	5.56	5.97	100	-0.10	-0.33	0.14	0.19	6.98	6.11	5.81	6.30
Average	0.32	0.26	0.16	0.25	10.20	8.98	8.67	9.28	Average	0.29	0.30	0.14	0.24	10.93	9.57	9.07	9.86
CCEMGX									*CCEPX*								
20	-0.40	0.19	-0.29	0.29	14.59	13.15	12.53	13.42	20	-0.69	0.26	-0.26	0.40	15.75	14.13	13.19	14.36
50	0.37	-0.41	0.06	0.28	9.80	8.07	7.95	8.61	50	0.05	-0.28	0.01	0.11	10.10	8.48	8.21	8.93
100	-0.12	-0.25	0.13	0.17	6.56	5.82	5.56	5.98	100	-0.11	-0.33	0.14	0.19	6.98	6.11	5.81	6.30
Average	0.30	0.28	0.16	0.25	10.32	9.01	8.68	9.34	Average	0.28	0.29	0.13	0.24	10.95	9.57	9.07	9.86
IPCMG									*IPCP*								
20	-0.96	0.20	-0.31	0.49	15.07	12.98	12.35	13.46	20	-1.01	-0.44	-0.51	0.65	16.43	15.52	14.57	15.50
50	0.27	-0.38	0.06	0.24	9.54	7.95	7.87	8.45	50	-0.17	-0.67	-0.32	0.38	10.66	9.23	9.25	9.71
100	-0.08	-0.23	0.13	0.15	6.29	5.72	5.52	5.85	100	-0.43	-0.52	0.05	0.33	7.33	6.94	6.71	6.99
Average	0.44	0.27	0.16	0.29	10.30	8.88	8.58	9.25	Average	0.54	0.54	0.29	0.46	11.47	10.56	10.18	10.74
PCMGX									*PCPX*								
20	1.59	1.13	-0.10	0.94	22.48	16.83	13.68	17.67	20	1.22	0.90	-0.25	0.79	20.86	16.62	13.86	17.11
50	1.21	0.02	0.22	0.49	15.36	10.15	8.70	11.40	50	0.83	0.08	0.12	0.35	13.72	10.03	8.82	10.85
100	0.85	0.21	0.17	0.41	10.34	7.23	6.20	7.93	100	0.80	0.05	0.18	0.35	9.70	7.15	6.31	7.72
Average	1.22	0.45	0.16	0.61	16.06	11.40	9.53	12.33	Average	0.95	0.35	0.18	0.49	14.76	11.27	9.66	11.90
PCMGX2S									*PCPX2S*								
20	-0.31	0.39	-0.26	0.32	15.73	13.35	12.40	13.83	20	-0.49	0.27	-0.35	0.37	16.00	14.15	12.87	14.34
50	0.24	-0.33	0.11	0.23	10.39	8.09	7.91	8.80	50	0.03	-0.30	-0.02	0.12	10.47	8.49	8.18	9.05
100	-0.06	-0.23	0.15	0.14	6.82	5.80	5.54	6.06	100	-0.04	-0.32	0.16	0.17	7.11	6.12	5.76	6.33
Average	0.20	0.32	0.17	0.23	10.98	9.08	8.62	9.56	Average	0.19	0.30	0.18	0.22	11.19	9.59	8.93	9.91
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	35.15	44.85	47.05	42.35	9.55	10.70	11.60	10.62	20	45.20	55.75	57.15	52.70	9.90	9.70	10.55	10.05
50	61.50	78.30	82.25	74.02	11.25	15.00	17.45	14.57	50	75.80	86.00	90.20	84.00	11.20	13.75	13.35	12.77
100	84.05	95.95	98.05	92.68	17.40	25.25	25.50	22.72	100	90.10	98.50	99.10	95.90	13.65	19.50	18.95	17.37
Average	60.23	73.03	75.78	69.68	12.73	16.98	18.18	15.97	Average	70.37	80.08	82.15	77.53	11.58	14.32	14.28	13.39
*SW**									*2WFE*								
20	41.15	47.50	49.00	45.88	9.30	10.75	11.75	10.60	20	47.05	63.90	74.10	61.68	8.40	9.05	9.20	8.88
50	71.00	81.05	83.80	78.62	12.50	14.85	17.40	14.92	50	45.40	63.60	72.75	60.58	13.80	17.05	16.05	15.63
100	89.45	97.20	98.35	95.00	16.15	25.30	25.25	22.23	100	45.55	63.90	75.50	61.65	26.30	26.60	31.45	28.12
Average	67.20	75.25	77.05	73.17	12.65	16.97	18.13	15.92	Average	46.00	63.80	74.12	61.31	16.17	17.57	18.90	17.54
CCEMG									*CCEP*								
20	6.35	7.90	7.95	7.40	10.40	10.70	10.30	10.47	20	7.50	7.95	8.25	7.90	9.00	10.90	10.05	9.98
50	6.10	5.80	6.65	6.18	16.45	21.65	22.35	20.15	50	5.85	5.85	6.50	6.07	17.65	20.85	21.25	19.92
100	5.10	6.40	4.90	5.47	32.65	36.40	44.10	37.72	100	5.20	5.65	5.55	5.47	29.25	34.20	39.95	34.47
Average	5.85	6.70	6.50	6.35	19.83	22.92	25.58	22.78	Average	6.18	6.48	6.77	6.48	18.63	21.98	23.75	21.46
CCEMGX									*CCEPX*								
20	4.90	6.15	6.90	5.98	10.35	10.75	10.45	10.52	20	5.65	6.60	6.95	6.40	9.10	10.90	10.00	10.00
50	6.00	5.25	6.15	5.80	16.95	21.30	22.30	20.18	50	5.30	5.10	5.95	5.45	17.55	20.40	21.35	19.77
100	4.95	6.15	4.70	5.27	31.50	35.15	44.55	37.07	100	4.80	5.25	5.10	5.05	29.50	34.25	39.95	34.57
Average	5.28	5.85	5.92	5.68	19.60	22.40	25.77	22.59	Average	5.25	5.65	6.00	5.63	18.72	21.85	23.77	21.44
IPCMG									*IPCP*								
20	5.15	6.50	6.85	6.17	9.55	10.05	11.25	10.28	20	8.15	10.30	9.95	9.47	7.85	9.55	10.05	9.15
50	6.05	5.30	5.75	5.70	15.85	21.75	23.00	20.20	50	7.25	6.25	7.55	7.02	15.15	18.60	15.45	16.40
100	5.05	5.85	4.85	5.25	34.85	39.00	44.10	39.32	100	6.25	7.30	7.10	6.88	26.85	26.15	32.75	28.58
Average	5.42	5.88	5.82	5.71	20.08	23.60	26.12	23.27	Average	7.22	7.95	8.20	7.79	16.62	18.10	19.42	18.04
PCMGX									*PCPX*								
20	5.45	6.00	5.85	5.77	8.35	10.35	9.90	9.53	20	5.95	6.05	5.90	5.97	8.30	9.65	9.85	9.27
50	5.40	5.10	5.55	5.35	11.20	15.55	19.90	15.55	50	5.25	5.15	5.00	5.13	11.85	14.75	20.60	15.73
100	5.30	5.05	5.15	5.17	18.75	28.55	34.70	27.33	100	5.05	4.75	5.35	5.05	21.45	27.80	33.65	27.63
Average	5.38	5.38	5.52	5.43	12.77	18.15	21.50	17.47	Average	5.42	5.32	5.42	5.38	13.87	17.40	21.37	17.54
PCMGX2S									*PCPX2S*								
20	5.80	6.30	6.80	6.30	9.20	12.20	10.80	10.73	20	6.65	7.35	7.45	7.15	9.25	11.00	9.80	10.02
50	5.80	5.25	6.05	5.70	14.80	21.45	23.65	19.97	50	6.00	5.20	6.25	5.82	15.70	20.80	20.45	18.98
100	5.00	6.00	4.50	5.17	29.80	36.65	44.75	37.07	100	5.10	5.65	5.45	5.40	27.95	34.55	39.70	34.07
Average	5.53	5.85	5.78	5.72	17.93	23.43	26.40	22.59	Average	5.92	6.07	6.38	6.12	17.63	22.12	23.32	21.02

Table A14: High Heterogeneity – DGP4, Case h: High Spatial Dependence & High Factor Dependence

	Heterogeneous									*Homogeneous*							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	35.67	36.34	34.45	35.49	45.20	43.04	39.43	42.55	20	43.01	45.22	43.70	43.97	52.25	51.66	48.81	50.91
50	37.25	35.61	34.73	35.86	43.05	38.65	37.10	39.60	50	44.82	45.14	44.34	44.77	50.97	48.55	46.96	48.83
100	35.85	35.75	35.26	35.62	39.78	37.76	36.71	38.09	100	44.19	45.03	45.14	44.79	49.15	47.40	46.85	47.80
Average	36.26	35.90	34.82	35.66	42.68	39.82	37.75	40.08	Average	44.01	45.13	44.39	44.51	50.79	49.20	47.54	49.18
*SW**									*2WFE*								
20	38.91	37.93	35.29	37.38	47.53	44.23	40.13	43.96	20	-0.30	0.31	-0.22	0.28	17.51	16.59	15.62	16.57
50	40.09	37.27	35.60	37.65	45.35	40.19	37.91	41.15	50	-0.05	-0.36	-0.31	0.24	11.57	10.15	9.94	10.55
100	38.94	37.28	36.16	37.46	42.79	39.23	37.59	39.87	100	-0.10	-0.27	0.13	0.17	7.91	7.22	7.19	7.44
Average	39.31	37.49	35.68	37.50	45.22	41.22	38.54	41.66	Average	0.15	0.31	0.22	0.23	12.33	11.32	10.91	11.52
CCEMG									*CCEP*								
20	-0.46	0.32	-0.32	0.37	16.54	13.66	12.70	14.30	20	-0.72	0.46	-0.30	0.49	16.98	14.55	13.36	14.96
50	0.39	-0.44	0.02	0.28	11.75	8.52	8.06	9.45	50	0.03	-0.30	-0.04	0.12	11.26	8.87	8.32	9.48
100	-0.05	-0.22	0.12	0.13	7.79	6.19	5.70	6.56	100	-0.08	-0.31	0.12	0.17	7.75	6.42	5.93	6.70
Average	0.30	0.33	0.16	0.26	12.03	9.46	8.82	10.10	Average	0.28	0.36	0.15	0.26	12.00	9.95	9.20	10.38
CCEMGX									*CCEPX*								
20	-0.22	0.43	-0.30	0.32	17.51	13.88	12.74	14.71	20	-0.79	0.44	-0.29	0.51	17.02	14.51	13.35	14.96
50	0.37	-0.46	0.02	0.28	12.21	8.59	8.09	9.63	50	0.01	-0.32	-0.03	0.12	11.28	8.86	8.33	9.49
100	-0.14	-0.24	0.12	0.16	7.89	6.20	5.70	6.60	100	-0.11	-0.31	0.11	0.18	7.74	6.41	5.92	6.69
Average	0.24	0.38	0.14	0.25	12.54	9.56	8.84	10.31	Average	0.30	0.36	0.14	0.27	12.01	9.92	9.20	10.38
IPCMG									*IPCP*								
20	-0.37	0.33	-0.33	0.34	15.61	13.75	12.92	14.09	20	-1.73	-1.24	-0.69	1.22	17.47	16.05	14.92	16.15
50	0.52	-0.15	0.32	0.33	10.83	8.58	8.30	9.24	50	-0.93	-0.95	-0.65	0.85	11.74	9.75	9.53	10.34
100	0.14	-0.14	0.20	0.16	7.29	6.09	5.71	6.36	100	-0.63	-0.62	-0.10	0.45	7.91	7.12	6.77	7.27
Average	0.35	0.21	0.29	0.28	11.24	9.47	8.98	9.90	Average	1.10	0.93	0.48	0.84	12.37	10.97	10.41	11.25
PCMGX									*PCPX*								
20	1.70	1.27	-0.06	1.01	25.87	17.85	14.04	19.25	20	1.17	1.00	-0.23	0.80	23.12	17.42	14.18	18.24
50	1.08	0.00	0.20	0.42	17.29	10.65	8.85	12.27	50	0.68	0.04	0.10	0.27	14.97	10.42	8.95	11.45
100	0.81	0.22	0.17	0.40	11.26	7.60	6.34	8.40	100	0.76	0.07	0.17	0.34	10.27	7.46	6.43	8.05
Average	1.20	0.50	0.14	0.61	18.14	12.04	9.74	13.31	Average	0.87	0.37	0.17	0.47	16.12	11.77	9.85	12.58
PCMGX2S									*PCPX2S*								
20	-0.06	0.47	-0.29	0.27	18.07	13.95	12.62	14.88	20	-0.29	0.41	-0.28	0.33	17.32	14.54	13.05	14.97
50	0.37	-0.31	0.06	0.25	12.70	8.57	8.01	9.76	50	-0.08	-0.32	-0.01	0.14	11.60	8.90	8.31	9.60
100	0.03	-0.21	0.14	0.13	8.25	6.20	5.69	6.71	100	-0.03	-0.30	0.13	0.15	7.98	6.47	5.90	6.78
Average	0.15	0.33	0.16	0.21	13.01	9.57	8.77	10.45	Average	0.13	0.34	0.14	0.21	12.30	9.97	9.09	10.45
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	32.05	44.05	46.35	40.82	9.95	10.50	10.70	10.38	20	43.45	54.55	56.80	51.60	9.70	10.15	11.30	10.38
50	58.70	76.55	81.70	72.32	10.90	13.85	17.55	14.10	50	74.20	84.95	90.00	83.05	10.65	13.55	13.85	12.68
100	81.45	94.60	97.90	91.32	16.10	24.35	25.10	21.85	100	89.10	98.25	99.00	95.45	12.85	19.95	19.60	17.47
Average	57.40	71.73	75.32	68.15	12.32	16.23	17.78	15.44	Average	68.92	79.25	81.93	76.70	11.07	14.55	14.92	13.51
*SW**									*2WFE*								
20	38.60	47.25	48.70	44.85	9.65	10.10	11.15	10.30	20	40.05	59.20	70.85	56.70	8.65	9.25	8.80	8.90
50	68.75	80.05	84.00	77.60	11.70	13.80	17.10	14.20	50	38.05	57.20	67.80	54.35	14.00	17.55	15.85	15.80
100	88.50	96.70	98.15	94.45	15.20	24.35	24.70	21.42	100	39.45	58.85	70.50	56.27	24.85	25.45	28.70	26.33
Average	65.28	74.67	76.95	72.30	12.18	16.08	17.65	15.31	Average	39.18	58.42	69.72	55.77	15.83	17.42	17.78	17.01
CCEMG									*CCEP*								
20	6.30	8.00	7.85	7.38	8.15	10.90	10.90	9.98	20	7.35	8.05	7.95	7.78	8.70	10.80	9.80	9.77
50	5.75	6.00	6.15	5.97	13.50	19.05	22.80	18.45	50	5.20	5.20	6.00	5.47	14.60	19.75	20.70	18.35
100	5.15	6.50	4.90	5.52	24.15	30.90	42.45	32.50	100	5.20	6.25	5.55	5.67	24.80	30.20	38.15	31.05
Average	5.73	6.83	6.30	6.29	15.27	20.28	25.38	20.31	Average	5.92	6.50	6.50	6.31	16.03	20.25	22.88	19.72
CCEMGX									*CCEPX*								
20	3.55	5.75	6.10	5.13	9.50	10.10	10.20	9.93	20	3.90	5.90	6.35	5.38	8.70	10.05	10.35	9.70
50	5.35	4.50	5.45	5.10	12.15	20.00	22.10	18.08	50	4.25	4.75	5.40	4.80	14.75	18.90	20.75	18.13
100	4.30	6.20	4.70	5.07	24.65	30.70	42.00	32.45	100	4.35	5.70	5.15	5.07	24.70	29.65	37.70	30.68
Average	4.40	5.48	5.42	5.10	15.43	20.27	24.77	20.16	Average	4.17	5.45	5.63	5.08	16.05	19.53	22.93	19.51
IPCMG									*IPCP*								
20	5.75	6.70	6.70	6.38	9.65	10.50	11.10	10.42	20	8.35	9.10	9.25	8.90	7.60	8.90	9.20	8.57
50	5.65	5.05	5.40	5.37	16.25	20.55	23.15	19.98	50	7.50	6.75	7.10	7.12	13.15	14.85	16.40	14.80
100	4.35	6.40	4.45	5.07	30.00	34.85	44.15	36.33	100	6.60	7.30	6.05	6.65	22.75	24.80	31.65	26.40
Average	5.25	6.05	5.52	5.61	18.63	21.97	26.13	22.24	Average	7.48	7.72	7.47	7.56	14.50	16.18	19.08	16.59
PCMGX									*PCPX*								
20	5.70	6.70	6.40	6.27	7.95	9.35	9.05	8.78	20	5.20	5.70	6.25	5.72	7.70	10.65	9.60	9.32
50	5.80	5.50	5.05	5.45	9.20	13.75	19.50	14.15	50	5.85	4.90	4.75	5.17	8.90	14.45	20.05	14.47
100	5.10	5.25	4.85	5.07	16.75	26.60	35.30	26.22	100	5.20	5.55	5.20	5.32	18.45	23.55	32.75	24.92
Average	5.53	5.82	5.43	5.59	11.30	16.57	21.28	16.38	Average	5.42	5.38	5.40	5.40	11.68	16.22	20.80	16.23
PCMGX2S									*PCPX2S*								
20	5.35	6.85	6.70	6.30	8.40	10.25	11.15	9.93	20	6.75	7.05	7.05	6.95	8.35	11.35	10.35	10.02
50	5.20	5.30	5.65	5.38	13.85	19.50	22.25	18.53	50	5.80	5.15	5.95	5.63	12.80	18.80	20.30	17.30
100	4.85	6.25	4.70	5.27	24.15	33.60	41.85	33.20	100	5.15	6.15	5.25	5.52	22.85	29.25	38.50	30.20
Average	5.13	6.13	5.68	5.65	15.47	21.12	25.08	20.56	Average	5.90	6.12	6.08	6.03	14.67	19.80	23.05	19.17

Table A15: Partially Heterogeneous Estimators – Low Heterogeneity – DGP1: No CSD

	$K = 2$								$K = 3$							
T	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.53	-0.11	0.01	0.22	12.58	10.40	9.99	10.99	0.23	-0.12	-0.01	0.12	12.42	10.11	9.54	10.69
50	-0.26	0.20	-0.16	0.21	6.92	6.52	6.58	6.67	-0.26	0.17	-0.23	0.22	6.81	6.24	6.30	6.45
100	-0.01	0.11	-0.03	0.05	5.13	4.72	4.42	4.76	-0.02	0.07	0.01	0.04	5.09	4.48	4.33	4.63
Average	0.27	0.14	0.07	0.16	8.21	7.21	7.00	7.47	0.17	0.12	0.08	0.12	8.11	6.94	6.73	7.26
C-Lasso CCE																
20	2.46	2.08	2.16	2.24	12.20	10.32	9.77	10.76	2.86	2.72	2.86	2.81	12.37	10.26	10.00	10.88
50	1.97	1.99	1.46	1.81	7.42	6.69	6.33	6.82	3.05	2.93	2.18	2.72	7.71	6.99	6.61	7.10
100	2.39	1.89	1.56	1.94	5.94	4.97	4.60	5.17	3.34	2.92	2.28	2.85	6.04	5.35	4.83	5.40
Average	2.27	1.99	1.73	2.00	8.52	7.33	6.90	7.58	3.09	2.86	2.44	2.79	8.71	7.54	7.14	7.80
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	36.20	40.40	41.30	39.30	9.60	10.10	10.60	10.10	40.30	46.30	50.80	45.80	9.70	8.70	7.40	8.60
50	27.30	37.20	41.30	35.27	22.70	19.80	18.60	20.37	27.70	43.00	47.60	39.43	23.50	14.00	16.90	18.13
100	27.70	33.00	42.10	34.27	38.60	31.10	38.30	36.00	27.80	37.20	44.50	36.50	32.70	30.20	34.40	32.43
Average	30.40	36.87	41.57	36.28	23.63	20.33	22.50	22.16	31.93	42.17	47.63	40.58	21.97	17.63	19.57	19.72
C-Lasso CCE																
20	19.50	20.00	19.40	19.63	11.10	15.50	14.80	13.80	32.60	33.40	35.50	33.83	8.30	12.10	9.90	10.10
50	12.70	14.00	13.60	13.43	26.10	20.00	28.40	24.83	24.80	27.90	25.80	26.17	20.50	21.90	17.70	20.03
100	16.70	14.50	14.10	15.10	31.80	30.70	43.60	35.37	22.70	26.90	25.10	24.90	27.50	34.80	37.50	33.27
Average	16.30	16.17	15.70	16.06	23.00	22.07	28.93	24.67	26.70	29.40	28.80	28.30	18.77	22.93	21.70	21.13

Table A16: Partially Heterogeneous Estimators – Low Heterogeneity – DGP2, Case a: Low Spatial Dependence

	$K = 2$								$K = 3$							
T	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	-0.21	0.10	-0.01	0.11	12.42	10.40	10.40	11.08	-0.13	-0.05	-0.07	0.08	12.09	10.17	10.03	10.76
50	0.10	0.17	0.27	0.18	7.50	6.53	6.40	6.81	0.15	0.20	0.20	0.18	7.44	6.34	6.02	6.60
100	0.13	0.01	-0.05	0.07	5.05	4.76	4.55	4.79	0.11	-0.04	-0.07	0.07	5.06	4.61	4.45	4.70
Average	0.15	0.10	0.11	0.12	8.32	7.23	7.12	7.56	0.13	0.10	0.11	0.11	8.20	7.04	6.83	7.36
C-Lasso CCE																
20	2.06	1.81	1.58	1.82	11.78	10.51	9.83	10.71	2.60	2.50	2.20	2.43	11.94	10.77	9.93	10.88
50	2.38	1.89	1.91	2.06	8.13	6.57	6.40	7.04	3.23	2.95	2.64	2.94	8.21	6.97	6.67	7.28
100	2.47	1.78	1.50	1.92	6.07	5.01	4.72	5.26	3.24	2.83	2.28	2.78	6.25	5.30	4.97	5.51
Average	2.30	1.83	1.66	1.93	8.66	7.36	6.98	7.67	3.02	2.76	2.37	2.72	8.80	7.68	7.19	7.89
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	34.40	38.20	42.30	38.30	9.50	11.70	10.00	10.40	37.60	45.90	50.20	44.57	9.30	10.90	8.70	9.63
50	25.90	35.60	41.90	34.47	17.80	15.40	16.90	16.70	29.10	41.10	48.60	39.60	20.20	17.00	14.40	17.20
100	20.60	31.80	39.30	30.57	40.00	39.40	32.80	37.40	22.10	37.30	45.20	34.87	34.90	32.90	24.70	30.83
Average	26.97	35.20	41.17	34.44	22.43	22.17	19.90	21.50	29.60	41.43	48.00	39.68	21.47	20.27	15.93	19.22
C-Lasso CCE																
20	17.90	20.60	19.80	19.43	12.50	12.80	13.30	12.87	30.70	34.60	35.60	33.63	10.00	10.10	11.00	10.37
50	13.90	15.10	15.90	14.97	19.60	20.70	25.10	21.80	24.80	28.00	26.10	26.30	17.50	20.60	20.10	19.40
100	14.90	14.40	12.50	13.93	28.20	40.00	39.80	36.00	22.00	24.70	22.80	23.17	30.20	32.00	35.10	32.43
Average	15.57	16.70	16.07	16.11	20.10	24.50	26.07	23.56	25.83	29.10	28.17	27.70	19.23	20.90	22.07	20.73

Table A17: Partially Heterogeneous Estimators – Low Heterogeneity – DGP2, Case *b*: High Spatial Dependence

	$K = 2$								$K = 3$							
	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.04	0.41	0.08	0.18	12.88	11.04	10.58	11.50	0.08	0.43	0.19	0.23	13.04	10.93	10.27	11.41
50	-0.32	-0.03	0.03	0.13	7.98	7.35	6.92	7.42	-0.32	-0.04	0.12	0.16	8.05	7.05	6.81	7.31
100	0.09	-0.19	-0.11	0.13	5.69	5.12	4.64	5.15	0.13	-0.20	-0.12	0.15	5.76	5.02	4.58	5.12
Average	0.15	0.21	0.07	0.15	8.85	7.84	7.38	8.02	0.18	0.22	0.14	0.18	8.95	7.67	7.22	7.95
C-Lasso CCE																
20	1.79	1.87	2.17	1.94	13.37	11.23	10.35	11.65	1.71	2.70	2.91	2.44	13.41	11.21	10.72	11.78
50	1.65	1.75	1.74	1.71	8.43	7.05	6.72	7.40	2.20	2.78	2.77	2.58	8.54	7.26	6.99	7.59
100	2.71	2.01	1.44	2.05	7.18	5.50	4.92	5.87	3.26	3.09	2.53	2.96	7.06	5.76	5.19	6.00
Average	2.05	1.87	1.78	1.90	9.66	7.93	7.33	8.30	2.39	2.86	2.74	2.66	9.67	8.07	7.63	8.46
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	26.20	27.60	34.20	29.33	11.10	10.90	11.30	11.10	31.20	37.10	43.50	37.27	10.40	9.90	9.00	9.77
50	17.00	31.40	34.30	27.57	22.50	17.30	17.50	19.10	16.00	33.80	40.10	29.97	19.20	15.70	18.20	17.70
100	14.60	23.80	30.50	22.97	33.10	38.60	36.70	36.13	13.20	24.90	33.50	23.87	29.20	30.80	34.70	31.57
Average	19.27	27.60	33.00	26.62	22.23	22.27	21.83	22.11	20.13	31.93	39.03	30.37	19.60	18.80	20.63	19.68
C-Lasso CCE																
20	19.90	20.60	20.10	20.20	11.40	12.60	11.80	11.93	29.50	34.10	34.90	32.83	6.30	11.70	9.20	9.07
50	12.70	13.30	12.90	12.97	19.20	23.20	20.60	21.00	17.80	24.00	26.10	22.63	18.40	18.20	19.30	18.63
100	14.90	13.90	13.80	14.20	28.30	40.70	34.60	34.53	16.30	25.50	25.30	22.37	26.90	37.50	31.80	32.07
Average	15.83	15.93	15.60	15.79	19.63	25.50	22.33	22.49	21.20	27.87	28.77	25.94	17.20	22.47	20.10	19.92

Table A18: Partially Heterogeneous Estimators – Low Heterogeneity – DGP3, Case *c*: Low Factor Dependence

	$K = 2$								$K = 3$							
	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.08	0.60	-0.10	0.26	12.82	11.09	10.21	11.37	-0.11	0.64	-0.03	0.26	12.48	10.82	9.83	11.04
50	0.07	0.11	0.15	0.11	7.66	6.74	6.51	6.97	0.03	0.22	0.08	0.11	7.52	6.51	6.33	6.78
100	0.06	0.06	0.01	0.04	5.39	4.86	4.70	4.98	-0.05	0.00	0.03	0.03	5.22	4.66	4.54	4.80
Average	0.07	0.25	0.09	0.14	8.62	7.56	7.14	7.78	0.06	0.29	0.05	0.13	8.40	7.33	6.90	7.54
C-Lasso CCE																
20	1.73	2.68	1.46	1.96	11.83	10.88	9.31	10.67	2.35	3.74	2.47	2.86	11.77	11.00	9.76	10.85
50	2.15	1.80	1.76	1.91	7.76	6.61	6.34	6.91	3.08	2.90	2.73	2.90	7.81	7.03	6.69	7.18
100	1.99	1.93	1.52	1.82	5.74	5.23	4.87	5.28	3.06	3.05	2.47	2.86	6.09	5.59	5.20	5.63
Average	1.96	2.14	1.58	1.89	8.44	7.57	6.84	7.62	2.83	3.23	2.56	2.87	8.56	7.87	7.22	7.88
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	33.20	34.70	35.50	34.47	10.30	9.40	12.20	10.63	37.80	43.10	42.50	41.13	7.80	7.90	8.20	7.97
50	25.60	31.70	34.20	30.50	18.10	17.90	24.20	20.07	28.10	37.70	38.90	34.90	19.30	17.10	17.40	17.93
100	23.30	28.30	29.60	27.07	31.10	32.50	40.20	34.60	20.40	30.70	33.80	28.30	30.40	33.90	29.30	31.20
Average	27.37	31.57	33.10	30.68	19.83	19.93	25.53	21.77	28.77	37.17	38.40	34.78	19.17	19.63	18.30	19.03
C-Lasso CCE																
20	21.40	21.50	18.40	20.43	10.40	13.60	13.70	12.57	34.20	37.70	34.50	35.47	10.10	11.20	11.10	10.80
50	16.00	12.60	13.40	14.00	20.90	24.80	21.00	22.23	26.60	27.90	27.00	27.17	19.40	20.20	15.10	18.23
100	13.50	15.60	13.00	14.03	33.00	35.50	33.70	34.07	24.80	27.30	27.20	26.43	28.80	32.80	28.20	29.93
Average	16.97	16.57	14.93	16.16	21.43	24.63	22.80	22.96	28.53	30.97	29.57	29.69	19.43	21.40	18.13	19.66

Table A19: Partially Heterogeneous Estimators – Low Heterogeneity – DGP3, Case d: High Factor Dependence

	$K = 2$								$K = 3$							
T	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.11	0.70	-0.09	0.30	13.60	11.64	10.64	11.96	-0.30	0.42	0.09	0.27	13.06	11.31	10.43	11.60
50	0.02	0.05	0.22	0.09	8.09	7.01	6.78	7.30	0.06	0.15	0.15	0.12	7.77	6.76	6.62	7.05
100	-0.11	-0.03	-0.06	0.07	5.64	5.08	5.10	5.27	-0.04	-0.05	-0.04	0.04	5.55	4.83	4.81	5.06
Average	0.08	0.26	0.12	0.15	9.11	7.91	7.51	8.18	0.13	0.21	0.09	0.14	8.79	7.63	7.29	7.91
C-Lasso CCE																
20	1.71	2.92	1.55	2.06	12.60	11.22	9.62	11.15	2.25	3.92	2.53	2.90	12.41	11.39	9.94	11.25
50	2.20	1.95	1.90	2.02	7.97	6.84	6.63	7.15	3.15	3.15	2.88	3.06	8.03	7.30	7.00	7.44
100	2.18	2.03	1.55	1.92	5.98	5.38	5.03	5.46	3.30	3.24	2.65	3.06	6.35	5.75	5.45	5.85
Average	2.03	2.30	1.67	2.00	8.85	7.81	7.10	7.92	2.90	3.44	2.69	3.01	8.93	8.15	7.46	8.18
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	28.70	29.50	33.30	30.50	9.20	9.00	12.10	10.10	35.70	38.90	38.30	37.63	8.80	9.00	8.20	8.67
50	20.80	26.60	28.20	25.20	19.50	15.50	21.70	18.90	24.90	30.80	31.30	29.00	21.90	15.80	16.10	17.93
100	20.90	23.50	25.00	23.13	33.60	38.10	41.00	37.57	18.60	22.70	24.70	22.00	33.00	35.70	38.30	35.67
Average	23.47	26.53	28.83	26.28	20.77	20.87	24.93	22.19	26.40	30.80	31.43	29.54	21.23	20.17	20.87	20.76
C-Lasso CCE																
20	20.00	21.90	18.50	20.13	10.30	13.40	10.80	11.50	32.60	37.20	34.60	34.80	9.30	9.10	9.00	9.13
50	16.20	14.60	14.40	15.07	21.90	21.60	17.70	20.40	24.80	28.10	27.20	26.70	22.50	18.00	14.40	18.30
100	13.60	15.80	12.50	13.97	29.30	30.00	37.30	32.20	25.50	27.80	26.90	26.73	29.40	28.70	26.70	28.27
Average	16.60	17.43	15.13	16.39	20.50	21.67	21.93	21.37	27.63	31.03	29.57	29.41	20.40	18.60	16.70	18.57

Table A20: Partially Heterogeneous Estimators – Low Heterogeneity – DGP4, Case f: Low Spatial Dependence & High Factor Dependence

	$K = 2$								$K = 3$							
T	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	-0.04	0.38	0.01	0.14	12.65	11.49	10.88	11.68	0.21	0.36	0.20	0.26	12.47	10.90	10.67	11.35
50	-0.02	0.10	-0.17	0.10	8.12	7.44	6.74	7.43	0.13	0.29	-0.21	0.21	8.01	7.32	6.59	7.30
100	-0.02	-0.24	0.14	0.14	5.83	4.98	4.90	5.23	-0.05	-0.33	0.13	0.17	5.79	4.87	4.72	5.12
Average	0.02	0.24	0.11	0.13	8.86	7.97	7.51	8.11	0.13	0.33	0.18	0.21	8.75	7.69	7.33	7.93
C-Lasso CCE																
20	2.90	1.77	1.79	2.15	11.98	10.95	10.69	11.21	3.18	2.77	2.87	2.94	12.15	11.03	11.04	11.41
50	2.15	1.82	1.55	1.84	8.10	6.99	6.46	7.19	3.24	3.07	2.65	2.99	8.31	7.40	6.83	7.51
100	2.11	1.68	1.81	1.87	5.98	5.18	5.05	5.40	3.13	2.82	2.65	2.87	6.30	5.45	5.29	5.68
Average	2.39	1.76	1.72	1.95	8.68	7.71	7.40	7.93	3.18	2.89	2.72	2.93	8.92	7.96	7.72	8.20
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	29.70	28.40	35.50	31.20	8.80	11.00	10.20	10.00	35.80	35.10	42.90	37.93	9.10	10.50	9.10	9.57
50	19.90	26.50	24.20	23.53	20.60	24.00	22.50	22.37	23.00	28.00	30.10	27.03	15.80	19.60	19.90	18.43
100	19.30	21.10	24.70	21.70	35.20	40.50	43.00	39.57	21.00	23.30	26.80	23.70	34.90	41.40	38.90	38.40
Average	22.97	25.33	28.13	25.48	21.53	25.17	25.23	23.98	26.60	28.80	33.27	29.56	19.93	23.83	22.63	22.13
C-Lasso CCE																
20	20.30	19.20	19.60	19.70	10.80	9.80	11.50	10.70	33.40	35.00	33.80	34.07	9.50	9.60	11.70	10.27
50	13.10	14.10	12.00	13.07	16.40	20.30	24.50	20.40	23.80	26.20	27.90	25.97	17.00	18.30	16.00	17.10
100	11.80	13.20	14.40	13.13	28.50	34.20	33.60	32.10	20.80	24.30	24.90	23.33	28.20	30.30	29.50	29.33
Average	15.07	15.50	15.33	15.30	18.57	21.43	23.20	21.07	26.00	28.50	28.87	27.79	18.23	19.40	19.07	18.90

Table A21: Partially Heterogeneous Estimators – Low Heterogeneity – DGP4, Case h: High Spatial Dependence & High Factor Dependence

	$K = 2$								$K = 3$							
	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.74	0.53	-0.26	0.51	14.00	11.77	11.35	12.37	0.33	0.50	-0.09	0.31	14.00	11.76	10.97	12.24
50	-0.25	-0.27	-0.36	0.29	8.24	7.31	7.00	7.52	-0.24	-0.26	-0.34	0.28	8.09	7.17	6.68	7.31
100	0.23	-0.26	-0.43	0.31	6.11	5.11	5.11	5.44	0.19	-0.28	-0.25	0.24	5.96	4.90	5.00	5.29
Average	0.41	0.35	0.35	0.37	9.45	8.06	7.82	8.44	0.25	0.35	0.23	0.28	9.35	7.94	7.55	8.28
C-Lasso CCE																
20	2.45	2.40	1.11	1.99	13.63	11.04	10.06	11.58	2.25	3.19	2.05	2.50	13.75	11.27	10.25	11.76
50	2.15	1.74	1.55	1.81	8.20	7.26	6.87	7.45	2.84	2.89	2.60	2.78	8.29	7.44	6.89	7.54
100	2.70	1.70	1.51	1.97	7.01	5.63	5.09	5.91	3.24	2.90	2.66	2.93	6.89	5.76	5.50	6.05
Average	2.43	1.95	1.39	1.92	9.61	7.98	7.34	8.31	2.78	3.00	2.44	2.74	9.64	8.16	7.55	8.45
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	26.30	25.70	31.10	27.70	9.10	10.90	9.90	9.97	32.00	32.40	34.30	32.90	9.30	9.20	9.80	9.43
50	15.40	19.30	23.50	19.40	21.70	18.70	17.00	19.13	17.40	23.50	26.20	22.37	17.70	20.30	17.00	18.33
100	15.50	20.40	23.20	19.70	30.60	42.60	38.50	37.23	14.30	21.60	22.00	19.30	30.20	35.40	44.10	36.57
Average	19.07	21.80	25.93	22.27	20.47	24.07	21.80	22.11	21.23	25.83	27.50	24.86	19.07	21.63	23.63	21.44
C-Lasso CCE																
20	19.10	20.80	17.80	19.23	11.40	12.10	10.40	11.30	30.60	34.20	35.50	33.43	9.30	11.70	11.20	10.73
50	13.80	12.70	13.00	13.17	19.40	22.50	20.00	20.63	19.70	23.60	27.60	23.63	18.40	19.20	15.70	17.77
100	13.00	14.10	12.40	13.17	28.70	33.00	36.90	32.87	19.00	23.80	23.80	22.20	29.90	31.40	25.10	28.80
Average	15.30	15.87	14.40	15.19	19.83	22.53	22.43	21.60	23.10	27.20	28.97	26.42	19.20	20.77	17.33	19.10

Table A22: Partially Heterogeneous Estimators – High Heterogeneity – DGP1: No CSD

	$K = 2$								$K = 3$							
	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	-0.64	0.37	-0.31	0.44	17.35	13.62	13.64	14.87	-0.51	0.23	-0.15	0.30	17.03	13.11	13.27	14.47
50	-0.41	0.35	-0.32	0.36	9.77	8.95	8.80	9.17	-0.55	0.47	-0.36	0.46	9.51	8.82	8.51	8.95
100	0.01	-0.04	0.01	0.02	6.85	6.57	6.24	6.55	0.02	-0.06	0.04	0.04	6.57	6.22	6.08	6.29
Average	0.35	0.25	0.21	0.27	11.32	9.71	9.56	10.20	0.36	0.25	0.18	0.27	11.04	9.38	9.29	9.90
C-Lasso CCE																
20	3.16	3.78	3.38	3.44	16.05	13.73	13.96	14.58	3.51	4.82	4.71	4.35	15.99	14.05	14.30	14.78
50	3.09	4.09	3.00	3.39	10.18	10.01	9.32	9.84	3.38	5.43	4.80	4.54	10.06	10.23	9.79	10.03
100	3.84	2.90	2.98	3.24	8.29	7.52	7.12	7.64	4.27	4.66	4.86	4.60	7.93	7.74	7.87	7.85
Average	3.36	3.59	3.12	3.36	11.51	10.42	10.13	10.69	3.72	4.97	4.79	4.49	11.33	10.67	10.65	10.88
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	37.20	38.70	51.00	42.30	9.80	9.10	8.10	9.00	44.00	47.10	56.20	49.10	8.20	8.20	7.50	7.97
50	29.80	40.10	37.00	35.63	16.70	14.10	12.60	14.47	31.30	46.40	46.00	41.23	13.90	14.00	14.40	14.10
100	28.20	37.80	43.00	36.33	23.60	20.00	20.90	21.50	30.70	40.30	46.40	39.13	18.30	17.60	17.70	17.87
Average	31.73	38.87	43.67	38.09	16.70	14.40	13.87	14.99	35.33	44.60	49.53	43.16	13.47	13.27	13.20	13.31
C-Lasso CCE																
20	18.60	17.90	17.40	17.97	9.30	9.90	10.20	9.80	30.40	29.00	30.80	30.07	9.60	10.40	9.40	9.80
50	12.40	15.60	13.80	13.93	15.20	16.00	18.20	16.47	17.60	27.20	24.20	23.00	15.00	16.50	17.80	16.43
100	13.80	16.30	16.40	15.50	23.20	26.00	26.50	25.23	18.10	21.50	27.70	22.43	24.40	22.20	26.60	24.40
Average	14.93	16.60	15.87	15.80	15.90	17.30	18.30	17.17	22.03	25.90	27.57	25.17	16.33	16.37	17.93	16.88

Table A23: Partially Heterogeneous Estimators – High Heterogeneity – DGP2, Case a: Low Spatial Dependence

	K = 2								*K = 3*							
	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	-0.24	0.00	-0.01	0.08	15.84	14.50	13.77	14.70	-0.13	0.07	0.14	0.11	15.45	14.21	13.61	14.42
50	-0.59	-0.10	0.00	0.23	9.55	9.05	8.77	9.12	-0.51	-0.11	-0.03	0.22	9.35	8.56	8.56	8.82
100	0.08	-0.07	-0.11	0.09	6.79	6.61	6.27	6.56	0.11	-0.09	-0.04	0.08	6.60	6.29	6.13	6.34
Average	0.31	0.06	0.04	0.13	10.73	10.05	9.60	10.13	0.25	0.09	0.07	0.14	10.46	9.69	9.44	9.86
C-Lasso CCE																
20	3.54	3.56	3.85	3.65	15.52	14.72	14.25	14.83	3.17	4.27	5.02	4.15	15.18	14.94	14.72	14.95
50	3.13	3.52	3.13	3.26	10.19	9.60	9.36	9.71	3.73	4.98	4.89	4.53	9.94	9.93	10.07	9.98
100	3.72	3.18	2.74	3.21	8.16	7.43	7.16	7.58	4.25	4.86	4.77	4.63	7.96	7.80	7.75	7.84
Average	3.46	3.42	3.24	3.37	11.29	10.58	10.26	10.71	3.71	4.70	4.89	4.44	11.02	10.89	10.85	10.92
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	36.70	42.50	45.70	41.63	9.50	8.00	9.00	8.83	41.40	46.90	53.90	47.40	8.50	6.60	9.20	8.10
50	29.20	40.80	43.70	37.90	13.10	11.80	14.30	13.07	32.60	45.30	50.20	42.70	12.20	14.20	16.20	14.20
100	28.40	36.80	40.30	35.17	22.10	23.50	20.70	22.10	29.40	40.90	47.10	39.13	20.90	22.80	18.60	20.77
Average	31.43	40.03	43.23	38.23	14.90	14.43	14.67	14.67	34.47	44.37	50.40	43.08	13.87	14.53	14.67	14.36
C-Lasso CCE																
20	19.00	19.30	16.30	18.20	8.80	10.10	9.80	9.57	27.70	30.50	28.60	28.93	9.20	10.70	9.60	9.83
50	13.00	14.50	14.20	13.90	16.30	17.90	18.50	17.57	17.80	21.90	24.10	21.27	15.90	17.70	15.60	16.40
100	14.10	14.10	16.20	14.80	19.10	24.70	24.40	22.73	20.80	24.40	27.20	24.13	21.20	31.40	24.60	25.73
Average	15.37	15.97	15.57	15.63	14.73	17.57	17.57	16.62	22.10	25.60	26.63	24.78	15.43	19.93	16.60	17.32

Table A24: Partially Heterogeneous Estimators – High Heterogeneity – DGP2, Case b: High Spatial Dependence

	K = 2								*K = 3*							
	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.10	-0.05	0.04	0.06	17.56	14.80	14.70	15.69	0.08	-0.03	0.08	0.06	17.03	14.32	14.46	15.27
50	0.02	0.15	0.20	0.12	10.88	9.41	9.15	9.81	0.06	-0.01	0.28	0.12	10.52	9.18	8.77	9.49
100	0.23	-0.01	-0.13	0.12	7.38	6.82	6.49	6.90	0.28	-0.03	-0.01	0.11	7.40	6.62	6.35	6.79
Average	0.12	0.07	0.12	0.10	11.94	10.34	10.11	10.80	0.14	0.02	0.12	0.10	11.65	10.04	9.86	10.52
C-Lasso CCE																
20	2.57	2.44	2.71	2.58	17.26	14.88	14.20	15.45	2.11	2.40	3.73	2.74	16.81	14.57	14.28	15.22
50	3.33	3.51	3.74	3.53	11.37	9.73	9.73	10.28	3.03	4.59	5.43	4.35	11.20	10.01	10.21	10.47
100	3.60	3.55	3.36	3.50	8.91	7.87	7.67	8.15	3.32	4.44	5.31	4.36	8.42	7.79	8.25	8.15
Average	3.17	3.17	3.27	3.20	12.51	10.83	10.53	11.29	2.82	3.81	4.82	3.82	12.14	10.79	10.91	11.28
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	28.00	31.30	37.10	32.13	9.10	8.10	9.10	8.77	31.30	39.80	46.00	39.03	9.30	8.80	8.80	8.97
50	21.50	29.30	38.10	29.63	13.60	13.50	14.20	13.77	21.40	32.70	40.00	31.37	13.60	13.20	14.70	13.83
100	17.50	31.80	39.50	29.60	26.10	27.40	21.20	24.90	14.90	30.50	39.20	28.20	23.90	27.70	24.70	25.43
Average	22.33	30.80	38.23	30.46	16.27	16.33	14.83	15.81	22.53	34.33	41.73	32.87	15.60	16.57	16.07	16.08
C-Lasso CCE																
20	17.30	17.70	17.10	17.37	10.60	9.60	12.20	10.80	28.90	27.60	30.40	28.97	5.90	10.90	9.70	8.83
50	13.50	13.80	16.00	14.43	14.40	14.80	16.50	15.23	18.00	22.20	25.60	21.93	16.50	17.40	14.80	16.23
100	14.30	14.70	17.30	15.43	18.70	29.30	29.10	25.70	15.50	20.60	27.10	21.07	24.60	26.30	27.20	26.03
Average	15.03	15.40	16.80	15.74	14.57	17.90	19.27	17.24	20.80	23.47	27.70	23.99	15.67	18.20	17.23	17.03

Table A25: Partially Heterogeneous Estimators – High Heterogeneity – DGP3, Case c: Low Factor Dependence

	$K = 2$								$K = 3$							
	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.26	0.86	0.09	0.40	16.86	14.83	13.94	15.21	0.03	1.07	-0.12	0.41	16.32	14.45	13.28	14.68
50	-0.10	0.14	0.26	0.17	10.32	9.22	8.95	9.50	0.05	0.19	0.26	0.17	9.87	8.81	8.49	9.06
100	0.00	0.09	0.24	0.11	7.24	6.30	6.54	6.69	-0.15	0.18	0.21	0.18	6.93	6.23	6.26	6.47
Average	0.12	0.36	0.20	0.23	11.48	10.12	9.81	10.47	0.08	0.48	0.20	0.25	11.04	9.83	9.34	10.07
C-Lasso CCE																
20	2.81	4.40	2.81	3.34	15.64	14.95	13.25	14.61	3.02	5.34	4.11	4.15	15.25	14.73	13.65	14.54
50	3.37	3.04	3.34	3.25	10.48	9.52	9.27	9.76	3.90	4.78	5.22	4.63	10.09	9.94	10.11	10.05
100	3.02	3.19	3.33	3.18	7.95	7.50	7.35	7.60	4.01	5.09	5.25	4.78	7.83	8.12	8.23	8.06
Average	3.07	3.54	3.16	3.26	11.36	10.66	9.96	10.66	3.64	5.07	4.86	4.52	11.06	10.93	10.67	10.88
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	36.40	36.20	40.60	37.73	7.80	9.10	9.20	8.70	40.00	44.10	44.30	42.80	8.30	8.80	9.70	8.93
50	30.50	35.10	35.30	33.63	13.60	12.40	13.20	13.07	31.80	39.10	39.50	36.80	13.10	10.90	13.00	12.33
100	28.30	32.10	38.10	32.83	25.50	20.00	19.80	21.77	29.60	35.60	36.00	33.73	22.20	22.70	18.00	20.97
Average	31.73	34.47	38.00	34.73	15.63	13.83	14.07	14.51	33.80	39.60	39.93	37.78	14.53	14.13	13.57	14.08
C-Lasso CCE																
20	17.30	18.00	16.20	17.17	9.00	11.60	9.50	10.03	26.60	32.00	28.50	29.03	8.20	10.20	10.00	9.47
50	16.40	13.00	13.50	14.30	15.70	16.40	16.20	16.10	20.20	23.50	26.50	23.40	14.40	13.60	14.70	14.23
100	13.30	13.90	15.00	14.07	25.00	28.80	22.10	25.30	20.40	25.30	25.40	23.70	20.70	22.30	18.30	20.43
Average	15.67	14.97	14.90	15.18	16.57	18.93	15.93	17.14	22.40	26.93	26.80	25.38	14.43	15.37	14.33	14.71

Table A26: Partially Heterogeneous Estimators – High Heterogeneity – DGP3, Case d: High Factor Dependence

	$K = 2$								$K = 3$							
	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.26	0.86	0.09	0.40	16.86	14.83	13.94	15.21	0.03	1.07	-0.12	0.41	16.32	14.45	13.28	14.68
50	-0.10	0.14	0.26	0.17	10.32	9.22	8.95	9.50	0.05	0.19	0.26	0.17	9.87	8.81	8.49	9.06
100	0.00	0.09	0.24	0.11	7.24	6.30	6.54	6.69	-0.15	0.18	0.21	0.18	6.93	6.23	6.26	6.47
Average	0.12	0.36	0.20	0.23	11.48	10.12	9.81	10.47	0.08	0.48	0.20	0.25	11.04	9.83	9.34	10.07
C-Lasso CCE																
20	2.81	4.40	2.81	3.34	15.64	14.95	13.25	14.61	3.02	5.34	4.11	4.15	15.25	14.73	13.65	14.54
50	3.37	3.04	3.34	3.25	10.48	9.52	9.27	9.76	3.90	4.78	5.22	4.63	10.09	9.94	10.11	10.05
100	3.02	3.19	3.33	3.18	7.95	7.50	7.35	7.60	4.01	5.09	5.25	4.78	7.83	8.12	8.23	8.06
Average	3.07	3.54	3.16	3.26	11.36	10.66	9.96	10.66	3.64	5.07	4.86	4.52	11.06	10.93	10.67	10.88
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	36.40	36.20	40.60	37.73	7.80	9.10	9.20	8.70	40.00	44.10	44.30	42.80	8.30	8.80	9.70	8.93
50	30.50	35.10	35.30	33.63	13.60	12.40	13.20	13.07	31.80	39.10	39.50	36.80	13.10	10.90	13.00	12.33
100	28.30	32.10	38.10	32.83	25.50	20.00	19.80	21.77	29.60	35.60	36.00	33.73	22.20	22.70	18.00	20.97
Average	31.73	34.47	38.00	34.73	15.63	13.83	14.07	14.51	33.80	39.60	39.93	37.78	14.53	14.13	13.57	14.08
C-Lasso CCE																
20	17.30	18.00	16.20	17.17	9.00	11.60	9.50	10.03	26.60	32.00	28.50	29.03	8.20	10.20	10.00	9.47
50	16.40	13.00	13.50	14.30	15.70	16.40	16.20	16.10	20.20	23.50	26.50	23.40	14.40	13.60	14.70	14.23
100	13.30	13.90	15.00	14.07	25.00	28.80	22.10	25.30	20.40	25.30	25.40	23.70	20.70	22.30	18.30	20.43
Average	15.67	14.97	14.90	15.18	16.57	18.93	15.93	17.14	22.40	26.93	26.80	25.38	14.43	15.37	14.33	14.71

Table A27: Partially Heterogeneous Estimators – High Heterogeneity – DGP4, Case f: Low Spatial Dependence & High Factor Dependence

	K = 2								*K = 3*							
T	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.45	0.38	-0.31	0.38	16.90	14.89	14.32	15.37	0.49	0.62	-0.05	0.39	16.15	14.34	13.95	14.81
50	-0.37	-0.13	-0.55	0.35	10.23	9.48	9.23	9.65	-0.36	-0.28	-0.55	0.40	9.74	9.08	8.82	9.21
100	0.30	-0.26	-0.40	0.32	7.48	6.62	6.65	6.92	0.15	-0.25	-0.33	0.24	7.19	6.53	6.49	6.74
Average	0.38	0.26	0.42	0.35	11.54	10.33	10.07	10.64	0.33	0.39	0.31	0.34	11.03	9.98	9.76	10.25
C-Lasso CCE																
20	3.11	4.21	2.97	3.43	15.80	14.60	14.28	14.89	3.09	4.29	4.37	3.91	16.02	14.39	14.52	14.97
50	3.23	2.85	2.30	2.80	10.16	9.61	9.25	9.67	3.63	4.38	4.44	4.15	9.57	9.66	9.71	9.64
100	3.63	2.86	2.67	3.05	8.32	7.58	7.22	7.71	4.34	4.63	4.90	4.62	8.02	7.90	8.08	8.00
Average	3.32	3.31	2.65	3.09	11.43	10.60	10.25	10.76	3.69	4.43	4.57	4.23	11.20	10.65	10.77	10.87
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	33.30	30.60	35.60	33.17	7.40	8.90	10.10	8.80	38.80	37.70	39.30	38.60	7.20	9.70	8.10	8.33
50	24.70	30.30	30.90	28.63	13.80	14.50	13.20	13.83	27.70	28.90	35.50	30.70	15.30	15.30	12.30	14.30
100	23.90	30.90	32.50	29.10	24.40	23.50	23.80	23.90	23.40	31.40	32.90	29.23	24.40	23.60	27.80	25.27
Average	27.30	30.60	33.00	30.30	15.20	15.63	15.70	15.51	29.97	32.67	35.90	32.84	15.63	16.20	16.07	15.97
C-Lasso CCE																
20	18.50	18.50	18.60	18.53	9.80	12.20	8.40	10.13	30.60	31.30	30.50	30.80	8.50	9.50	9.40	9.13
50	13.40	12.50	13.10	13.00	16.90	16.00	15.00	15.97	20.00	23.40	24.70	22.70	13.60	18.80	13.90	15.43
100	12.10	15.20	13.60	13.63	23.70	20.80	24.80	23.10	18.80	23.70	26.40	22.97	18.70	20.90	21.50	20.37
Average	14.67	15.40	15.10	15.06	16.80	16.33	16.07	16.40	23.13	26.13	27.20	25.49	13.60	16.40	14.93	14.98

Table A28: Partially Heterogeneous Estimators – High Heterogeneity – DGP4, Case h: High Spatial Dependence & High Factor Dependence

	K = 2								*K = 3*							
T	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.77	0.31	-0.22	0.43	17.76	15.16	14.50	15.81	0.48	0.48	-0.28	0.41	17.68	15.00	14.33	15.67
50	-0.45	-0.26	-0.57	0.43	10.60	9.57	9.30	9.82	-0.28	-0.32	-0.57	0.39	10.47	9.28	8.90	9.55
100	0.34	-0.24	-0.03	0.20	7.76	6.78	6.75	7.10	0.24	-0.27	-0.19	0.23	7.63	6.60	6.50	6.91
Average	0.52	0.27	0.27	0.35	12.04	10.50	10.18	10.91	0.34	0.36	0.34	0.35	11.93	10.30	9.91	10.71
C-Lasso CCE																
20	3.36	3.86	2.58	3.27	16.91	14.76	14.27	15.31	2.30	4.06	3.50	3.29	16.88	14.59	14.09	15.19
50	3.01	2.86	2.50	2.79	10.30	9.86	9.51	9.89	3.21	3.89	4.28	3.79	10.14	9.54	9.64	9.77
100	3.73	2.96	2.82	3.17	8.81	7.83	7.65	8.10	3.85	4.09	4.92	4.29	8.35	7.63	8.25	8.08
Average	3.37	3.23	2.63	3.08	12.01	10.82	10.48	11.10	3.12	4.01	4.23	3.79	11.79	10.59	10.66	11.01
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	30.00	29.30	33.10	30.80	10.40	8.80	9.30	9.50	34.10	34.30	36.60	35.00	7.60	7.90	9.20	8.23
50	22.00	27.30	30.70	26.67	16.70	14.70	13.70	15.03	23.30	26.60	30.80	26.90	14.50	12.50	16.80	14.60
100	21.20	29.20	31.30	27.23	20.70	21.20	21.30	21.07	19.80	25.30	30.70	25.27	22.30	23.90	24.10	23.43
Average	24.40	28.60	31.70	28.23	15.93	14.90	14.77	15.20	25.73	28.73	32.70	29.06	14.80	14.77	16.70	15.42
C-Lasso CCE																
20	18.50	19.20	17.20	18.30	10.30	10.80	8.10	9.73	28.60	29.80	29.50	29.30	7.70	9.40	9.50	8.87
50	13.70	11.60	13.00	12.77	15.40	14.50	14.70	14.87	17.80	20.50	23.70	20.67	13.50	17.20	11.90	14.20
100	13.30	15.60	15.00	14.63	20.50	22.60	24.30	22.47	17.50	20.30	23.90	20.57	22.10	21.10	19.20	20.80
Average	15.17	15.47	15.07	15.23	15.40	15.97	15.70	15.69	21.30	23.53	25.70	23.51	14.43	15.90	13.53	14.62

Table A29: Forecasting Accuracy Measures, Low Heterogeneity – DGP1: No CSD

	Heterogeneous									*Homogeneous*							
	RMSE				Theil's U					RMSE				Theil's U			
N \ T	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	1.090	1.083	1.010	1.061	0.431	0.416	0.379	0.409	20	1.141	1.181	1.124	1.149	0.453	0.454	0.422	0.443
50	1.138	0.993	0.981	1.038	0.425	0.386	0.375	0.395	50	1.182	1.106	1.106	1.131	0.442	0.431	0.422	0.432
100	1.115	1.038	0.979	1.044	0.416	0.380	0.388	0.395	100	1.166	1.147	1.103	1.138	0.437	0.421	0.437	0.432
Average	1.114	1.038	0.990	1.048	0.424	0.394	0.380	0.399	Average	1.163	1.144	1.111	1.139	0.444	0.435	0.427	0.435
Ind. GLS									*2WFE*								
20	1.058	1.078	1.009	1.048	0.419	0.415	0.378	0.404	20	1.223	1.263	1.230	1.239	0.484	0.485	0.459	0.476
50	1.099	0.990	0.981	1.023	0.410	0.385	0.374	0.390	50	1.234	1.181	1.214	1.210	0.460	0.458	0.459	0.459
100	1.077	1.034	0.978	1.030	0.402	0.378	0.387	0.389	100	1.208	1.216	1.175	1.200	0.451	0.445	0.464	0.453
Average	1.078	1.034	0.989	1.034	0.410	0.393	0.380	0.394	Average	1.222	1.220	1.206	1.216	0.465	0.463	0.461	0.463
Ind. CCE									*CCEP*								
20	1.165	1.118	1.027	1.103	0.461	0.430	0.385	0.425	20	1.189	1.204	1.129	1.174	0.473	0.464	0.423	0.453
50	1.210	1.026	0.997	1.078	0.452	0.399	0.381	0.411	50	1.234	1.134	1.118	1.162	0.462	0.442	0.427	0.444
100	1.181	1.075	0.995	1.084	0.441	0.393	0.394	0.410	100	1.216	1.183	1.118	1.172	0.456	0.434	0.444	0.444
Average	1.185	1.073	1.006	1.088	0.451	0.407	0.387	0.415	Average	1.213	1.174	1.122	1.169	0.464	0.447	0.431	0.447
Ind. CCEX									*CCEPX*								
20	1.172	1.119	1.027	1.106	0.464	0.430	0.385	0.426	20	1.189	1.204	1.129	1.174	0.473	0.464	0.423	0.453
50	1.216	1.027	0.998	1.080	0.455	0.399	0.381	0.412	50	1.234	1.134	1.118	1.162	0.462	0.442	0.427	0.444
100	1.185	1.075	0.995	1.085	0.443	0.394	0.394	0.410	100	1.216	1.183	1.118	1.172	0.456	0.434	0.444	0.444
Average	1.191	1.074	1.007	1.090	0.454	0.408	0.387	0.416	Average	1.213	1.174	1.122	1.169	0.464	0.447	0.431	0.447
Ind. IPC									*IPCP*								
20	1.236	1.128	1.030	1.131	0.485	0.434	0.386	0.435	20	1.191	1.205	1.130	1.175	0.474	0.464	0.424	0.454
50	1.230	1.029	0.998	1.086	0.460	0.400	0.381	0.414	50	1.234	1.134	1.118	1.162	0.462	0.442	0.427	0.444
100	1.186	1.075	0.995	1.085	0.443	0.394	0.394	0.410	100	1.216	1.183	1.118	1.172	0.456	0.434	0.444	0.444
Average	1.217	1.077	1.008	1.101	0.463	0.409	0.387	0.420	Average	1.214	1.174	1.122	1.170	0.464	0.447	0.431	0.447
Ind. PCX									*PCPX*								
20	1.194	1.123	1.029	1.115	0.472	0.432	0.386	0.430	20	1.190	1.204	1.129	1.175	0.473	0.464	0.424	0.454
50	1.242	1.030	0.999	1.091	0.465	0.401	0.382	0.416	50	1.234	1.134	1.118	1.162	0.462	0.442	0.427	0.444
100	1.213	1.079	0.996	1.096	0.453	0.395	0.395	0.414	100	1.216	1.183	1.118	1.172	0.456	0.434	0.444	0.445
Average	1.216	1.077	1.008	1.101	0.463	0.409	0.387	0.420	Average	1.213	1.174	1.122	1.170	0.464	0.447	0.431	0.447
Ind. PCX2S									*PCPX2S*								
20	1.225	1.128	1.030	1.128	0.484	0.434	0.387	0.435	20	1.192	1.205	1.130	1.176	0.474	0.464	0.424	0.454
50	1.271	1.034	1.000	1.102	0.475	0.402	0.382	0.420	50	1.235	1.134	1.118	1.162	0.462	0.442	0.427	0.444
100	1.238	1.081	0.997	1.106	0.462	0.396	0.395	0.418	100	1.216	1.183	1.118	1.172	0.456	0.434	0.444	0.445
Average	1.244	1.081	1.009	1.112	0.474	0.411	0.388	0.424	Average	1.214	1.174	1.122	1.170	0.464	0.447	0.431	0.447

Table A30: Forecasting Accuracy Measures, Low Heterogeneity – DGP2, Case a: Low Spatial Dependence

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	1.156	0.990	0.956	1.034	0.454	0.424	0.364	0.414	20	1.199	1.095	1.079	1.125	0.471	0.468	0.411	0.450
50	1.121	1.030	1.008	1.053	0.414	0.388	0.400	0.401	50	1.174	1.139	1.128	1.147	0.436	0.431	0.448	0.438
100	1.105	1.012	1.005	1.041	0.430	0.379	0.389	0.399	100	1.158	1.122	1.126	1.135	0.451	0.422	0.437	0.437
Average	1.127	1.011	0.990	1.043	0.433	0.397	0.384	0.405	Average	1.177	1.119	1.111	1.135	0.452	0.440	0.432	0.442
Ind. GLS									*2WFE*								
20	1.123	0.985	0.956	1.021	0.440	0.422	0.363	0.409	20	1.285	1.187	1.176	1.216	0.502	0.504	0.446	0.484
50	1.088	1.026	1.007	1.040	0.402	0.387	0.399	0.396	50	1.231	1.208	1.209	1.216	0.456	0.455	0.479	0.463
100	1.069	1.008	1.004	1.027	0.416	0.378	0.389	0.394	100	1.215	1.195	1.202	1.204	0.471	0.446	0.465	0.461
Average	1.093	1.006	0.989	1.030	0.420	0.395	0.384	0.400	Average	1.244	1.197	1.196	1.212	0.476	0.469	0.463	0.469
Ind. CCE									*CCEP*								
20	1.231	1.022	0.971	1.075	0.484	0.438	0.369	0.430	20	1.254	1.113	1.084	1.150	0.493	0.477	0.413	0.461
50	1.189	1.063	1.024	1.092	0.440	0.401	0.406	0.416	50	1.228	1.169	1.141	1.179	0.456	0.442	0.453	0.451
100	1.170	1.047	1.021	1.079	0.456	0.393	0.396	0.415	100	1.206	1.156	1.141	1.168	0.470	0.434	0.444	0.449
Average	1.197	1.044	1.006	1.082	0.460	0.411	0.390	0.420	Average	1.229	1.146	1.122	1.166	0.473	0.451	0.437	0.454
Ind. CCEX									*CCEPX*								
20	1.240	1.024	0.971	1.078	0.487	0.439	0.369	0.432	20	1.255	1.113	1.084	1.151	0.493	0.477	0.413	0.461
50	1.194	1.064	1.025	1.094	0.442	0.401	0.407	0.417	50	1.228	1.169	1.141	1.179	0.456	0.442	0.453	0.451
100	1.174	1.048	1.021	1.081	0.457	0.393	0.396	0.415	100	1.206	1.156	1.141	1.168	0.470	0.434	0.444	0.449
Average	1.203	1.045	1.006	1.085	0.462	0.411	0.391	0.421	Average	1.230	1.146	1.122	1.166	0.473	0.451	0.437	0.454
Ind. IPC									*IPCP*								
20	1.279	1.028	0.973	1.094	0.503	0.441	0.370	0.438	20	1.256	1.114	1.084	1.151	0.493	0.477	0.413	0.461
50	1.205	1.065	1.025	1.098	0.445	0.402	0.407	0.418	50	1.228	1.169	1.141	1.179	0.456	0.442	0.453	0.451
100	1.173	1.048	1.021	1.081	0.457	0.393	0.396	0.415	100	1.206	1.156	1.141	1.168	0.470	0.434	0.444	0.449
Average	1.219	1.047	1.007	1.091	0.468	0.412	0.391	0.424	Average	1.230	1.146	1.122	1.166	0.473	0.451	0.437	0.454
Ind. PCX									*PCPX*								
20	1.261	1.028	0.973	1.087	0.495	0.441	0.370	0.435	20	1.255	1.113	1.084	1.151	0.493	0.477	0.413	0.461
50	1.216	1.068	1.026	1.103	0.450	0.403	0.407	0.420	50	1.228	1.169	1.141	1.179	0.457	0.442	0.453	0.451
100	1.202	1.052	1.023	1.092	0.469	0.394	0.396	0.420	100	1.206	1.156	1.141	1.168	0.470	0.434	0.444	0.450
Average	1.226	1.049	1.007	1.094	0.471	0.413	0.391	0.425	Average	1.230	1.146	1.122	1.166	0.473	0.451	0.437	0.454
Ind. PCX2S									*PCPX2S*								
20	1.288	1.031	0.974	1.098	0.506	0.442	0.370	0.440	20	1.257	1.114	1.084	1.151	0.494	0.477	0.413	0.461
50	1.240	1.071	1.027	1.112	0.459	0.404	0.407	0.423	50	1.229	1.169	1.141	1.179	0.457	0.442	0.453	0.451
100	1.227	1.055	1.023	1.102	0.478	0.395	0.396	0.423	100	1.207	1.156	1.141	1.168	0.471	0.434	0.444	0.450
Average	1.252	1.052	1.008	1.104	0.481	0.414	0.391	0.429	Average	1.231	1.146	1.122	1.166	0.474	0.451	0.437	0.454

Table A31: Forecasting Accuracy Measures, Low Heterogeneity – DGP2, Case *b*: High Spatial Dependence

	Heterogeneous									*Homogeneous*							
	RMSE				Theil's U					RMSE				Theil's U			
N \ T	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	2.154	1.919	1.680	1.918	0.692	0.651	0.547	0.630	20	2.065	1.944	1.744	1.918	0.663	0.658	0.568	0.630
50	1.858	1.690	1.653	1.734	0.606	0.557	0.567	0.577	50	1.803	1.735	1.721	1.753	0.588	0.572	0.591	0.584
100	1.780	1.596	1.604	1.660	0.608	0.534	0.546	0.563	100	1.729	1.647	1.674	1.683	0.590	0.551	0.571	0.571
Average	1.931	1.735	1.645	1.770	0.635	0.581	0.553	0.590	Average	1.866	1.775	1.713	1.785	0.614	0.594	0.576	0.595
Ind. GLS									*2WFE*								
20	2.055	1.900	1.677	1.877	0.659	0.644	0.546	0.616	20	2.361	2.297	2.048	2.235	0.761	0.783	0.669	0.738
50	1.773	1.676	1.650	1.700	0.578	0.552	0.566	0.565	50	1.921	1.882	1.885	1.896	0.629	0.621	0.648	0.633
100	1.692	1.583	1.600	1.625	0.577	0.529	0.545	0.550	100	1.800	1.745	1.790	1.778	0.613	0.584	0.610	0.602
Average	1.840	1.720	1.642	1.734	0.605	0.575	0.552	0.577	Average	2.027	1.975	1.908	1.970	0.668	0.663	0.643	0.658
Ind. CCE									*CCEP*								
20	2.226	1.964	1.701	1.964	0.716	0.667	0.554	0.646	20	2.182	2.003	1.766	1.983	0.701	0.680	0.575	0.652
50	1.946	1.738	1.677	1.787	0.636	0.573	0.576	0.595	50	1.896	1.789	1.746	1.810	0.620	0.590	0.600	0.603
100	1.869	1.649	1.628	1.715	0.639	0.552	0.555	0.582	100	1.808	1.704	1.701	1.738	0.618	0.571	0.580	0.590
Average	2.014	1.784	1.669	1.822	0.664	0.597	0.561	0.607	Average	1.962	1.832	1.737	1.844	0.646	0.614	0.585	0.615
Ind. CCEX									*CCEPX*								
20	2.312	1.987	1.708	2.002	0.745	0.675	0.556	0.658	20	2.182	2.003	1.766	1.984	0.702	0.680	0.575	0.652
50	1.979	1.746	1.681	1.802	0.647	0.576	0.577	0.600	50	1.896	1.789	1.746	1.810	0.620	0.590	0.600	0.603
100	1.891	1.654	1.630	1.725	0.647	0.553	0.555	0.585	100	1.808	1.704	1.701	1.738	0.618	0.571	0.580	0.590
Average	2.060	1.796	1.673	1.843	0.679	0.601	0.563	0.615	Average	1.962	1.832	1.737	1.844	0.647	0.614	0.585	0.615
Ind. IPC									*IPCP*								
20	2.197	1.956	1.699	1.951	0.707	0.664	0.553	0.641	20	2.180	2.003	1.765	1.983	0.701	0.679	0.575	0.652
50	1.914	1.732	1.675	1.774	0.625	0.571	0.575	0.591	50	1.895	1.789	1.746	1.810	0.620	0.590	0.600	0.603
100	1.840	1.644	1.627	1.704	0.629	0.550	0.554	0.578	100	1.808	1.704	1.701	1.737	0.618	0.571	0.580	0.590
Average	1.984	1.778	1.667	1.809	0.654	0.595	0.561	0.603	Average	1.961	1.832	1.737	1.843	0.646	0.613	0.585	0.615
Ind. PCX									*PCPX*								
20	2.349	1.996	1.710	2.019	0.757	0.678	0.557	0.664	20	2.186	2.004	1.766	1.985	0.703	0.680	0.575	0.653
50	2.016	1.752	1.683	1.817	0.660	0.578	0.578	0.605	50	1.897	1.789	1.746	1.811	0.620	0.590	0.600	0.603
100	1.936	1.660	1.632	1.743	0.663	0.555	0.556	0.591	100	1.809	1.704	1.701	1.738	0.618	0.571	0.580	0.590
Average	2.100	1.803	1.675	1.859	0.693	0.604	0.564	0.620	Average	1.964	1.832	1.738	1.845	0.647	0.614	0.585	0.615
Ind. PCX2S									*PCPX2S*								
20	2.254	1.964	1.701	1.973	0.726	0.667	0.554	0.649	20	2.182	2.003	1.765	1.983	0.702	0.680	0.575	0.652
50	1.983	1.740	1.677	1.800	0.649	0.574	0.576	0.600	50	1.896	1.789	1.746	1.810	0.620	0.590	0.600	0.603
100	1.932	1.655	1.630	1.739	0.661	0.554	0.555	0.590	100	1.809	1.704	1.701	1.738	0.618	0.571	0.580	0.590
Average	2.056	1.786	1.670	1.837	0.679	0.598	0.562	0.613	Average	1.962	1.832	1.737	1.844	0.647	0.614	0.585	0.615

Table A32: Forecasting Accuracy Measures, Low Heterogeneity – DGP3, Case c: Low Factor Dependence

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	1.885	1.771	1.664	1.773	0.561	0.526	0.497	0.528	20	2.023	1.969	1.893	1.962	0.603	0.584	0.565	0.584
50	1.912	1.762	1.695	1.789	0.560	0.520	0.509	0.530	50	2.054	1.977	1.932	1.987	0.600	0.584	0.579	0.587
100	1.906	1.729	1.670	1.768	0.559	0.510	0.493	0.520	100	2.039	1.949	1.912	1.967	0.597	0.573	0.563	0.578
Average	1.901	1.754	1.677	1.777	0.560	0.519	0.500	0.526	Average	2.039	1.965	1.912	1.972	0.600	0.580	0.569	0.583
Ind. GLS									*2WFE*								
20	1.837	1.762	1.662	1.754	0.547	0.523	0.497	0.522	20	2.317	2.329	2.298	2.314	0.687	0.686	0.683	0.686
50	1.860	1.752	1.693	1.768	0.544	0.517	0.508	0.523	50	2.349	2.312	2.304	2.322	0.683	0.681	0.689	0.684
100	1.848	1.719	1.668	1.745	0.541	0.507	0.492	0.513	100	2.317	2.315	2.279	2.304	0.675	0.677	0.668	0.673
Average	1.848	1.744	1.674	1.756	0.544	0.516	0.499	0.520	Average	2.328	2.319	2.294	2.313	0.682	0.681	0.680	0.681
Ind. CCE									*CCEP*								
20	1.391	1.178	1.035	1.201	0.416	0.357	0.312	0.362	20	1.423	1.270	1.147	1.280	0.426	0.384	0.346	0.386
50	1.410	1.127	1.053	1.197	0.417	0.337	0.321	0.358	50	1.439	1.231	1.170	1.280	0.424	0.368	0.357	0.383
100	1.406	1.073	1.000	1.160	0.414	0.321	0.299	0.344	100	1.427	1.185	1.125	1.246	0.420	0.354	0.336	0.370
Average	1.403	1.126	1.029	1.186	0.416	0.338	0.311	0.355	Average	1.430	1.229	1.147	1.269	0.423	0.369	0.346	0.380
Ind. CCEX									*CCEPX*								
20	1.399	1.180	1.036	1.205	0.418	0.357	0.313	0.363	20	1.423	1.270	1.147	1.280	0.426	0.384	0.346	0.386
50	1.413	1.128	1.053	1.198	0.418	0.337	0.321	0.359	50	1.439	1.231	1.170	1.280	0.424	0.368	0.357	0.383
100	1.408	1.074	1.000	1.161	0.415	0.321	0.299	0.345	100	1.427	1.185	1.125	1.246	0.420	0.354	0.336	0.370
Average	1.407	1.127	1.030	1.188	0.417	0.339	0.311	0.355	Average	1.430	1.229	1.147	1.269	0.423	0.369	0.346	0.380
Ind. IPC									*IPCP*								
20	1.414	1.177	1.033	1.208	0.422	0.357	0.312	0.364	20	1.425	1.271	1.148	1.281	0.427	0.384	0.347	0.386
50	1.395	1.123	1.050	1.189	0.412	0.336	0.320	0.356	50	1.440	1.231	1.171	1.281	0.424	0.368	0.357	0.383
100	1.375	1.067	0.997	1.146	0.405	0.319	0.298	0.340	100	1.427	1.186	1.125	1.246	0.420	0.354	0.336	0.370
Average	1.394	1.122	1.027	1.181	0.413	0.337	0.310	0.353	Average	1.431	1.229	1.148	1.269	0.424	0.369	0.347	0.380
Ind. PCX									*PCPX*								
20	1.552	1.225	1.056	1.278	0.463	0.370	0.318	0.384	20	1.429	1.271	1.147	1.282	0.428	0.384	0.347	0.386
50	1.551	1.179	1.077	1.269	0.458	0.352	0.328	0.379	50	1.441	1.231	1.170	1.281	0.425	0.369	0.357	0.383
100	1.551	1.128	1.025	1.235	0.456	0.336	0.306	0.366	100	1.428	1.186	1.125	1.246	0.420	0.354	0.336	0.370
Average	1.551	1.177	1.053	1.260	0.459	0.353	0.318	0.376	Average	1.433	1.229	1.147	1.270	0.424	0.369	0.347	0.380
Ind. PCX2S									*PCPX2S*								
20	1.452	1.184	1.035	1.224	0.433	0.359	0.312	0.368	20	1.425	1.269	1.146	1.280	0.427	0.384	0.346	0.386
50	1.445	1.131	1.053	1.210	0.427	0.338	0.321	0.362	50	1.440	1.231	1.170	1.280	0.424	0.368	0.357	0.383
100	1.433	1.076	1.000	1.170	0.422	0.321	0.299	0.347	100	1.427	1.185	1.125	1.246	0.420	0.354	0.336	0.370
Average	1.443	1.131	1.029	1.201	0.428	0.339	0.311	0.359	Average	1.431	1.228	1.147	1.269	0.424	0.369	0.346	0.380

Table A33: Forecasting Accuracy Measures, Low Heterogeneity – DGP3, Case *d*: High Factor Dependence

	Heterogeneous									*Homogeneous*							
	RMSE				Theil's U					RMSE				Theil's U			
N \ T	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	3.154	2.899	2.762	2.938	0.747	0.684	0.657	0.696	20	3.259	3.117	3.020	3.132	0.771	0.734	0.718	0.741
50	3.188	2.912	2.793	2.964	0.748	0.684	0.666	0.699	50	3.306	3.146	3.065	3.173	0.773	0.738	0.729	0.747
100	3.171	2.884	2.781	2.945	0.745	0.677	0.656	0.693	100	3.265	3.119	3.054	3.146	0.764	0.731	0.720	0.738
Average	3.171	2.898	2.778	2.949	0.747	0.682	0.660	0.696	Average	3.277	3.127	3.047	3.150	0.769	0.734	0.722	0.742
Ind. GLS									*2WFE*								
20	3.064	2.881	2.756	2.900	0.725	0.679	0.656	0.686	20	3.881	3.887	3.864	3.877	0.918	0.916	0.921	0.918
50	3.094	2.892	2.787	2.924	0.724	0.679	0.664	0.689	50	3.932	3.883	3.853	3.889	0.922	0.916	0.920	0.919
100	3.063	2.863	2.774	2.900	0.718	0.672	0.654	0.681	100	3.869	3.904	3.841	3.871	0.908	0.916	0.908	0.911
Average	3.074	2.878	2.773	2.908	0.722	0.676	0.658	0.686	Average	3.894	3.891	3.853	3.879	0.916	0.916	0.917	0.916
Ind. CCE									*CCEP*								
20	1.771	1.313	1.128	1.404	0.422	0.319	0.275	0.339	20	1.792	1.393	1.228	1.471	0.427	0.338	0.300	0.355
50	1.769	1.231	1.102	1.367	0.420	0.296	0.271	0.329	50	1.791	1.325	1.213	1.443	0.423	0.319	0.298	0.347
100	1.733	1.162	1.035	1.310	0.410	0.279	0.251	0.314	100	1.749	1.265	1.156	1.390	0.413	0.304	0.281	0.332
Average	1.758	1.236	1.088	1.361	0.417	0.298	0.266	0.327	Average	1.777	1.328	1.199	1.435	0.421	0.320	0.293	0.345
Ind. CCEX									*CCEPX*								
20	1.789	1.319	1.131	1.413	0.427	0.321	0.276	0.341	20	1.792	1.393	1.228	1.471	0.427	0.338	0.300	0.355
50	1.776	1.234	1.103	1.371	0.421	0.297	0.271	0.330	50	1.791	1.325	1.213	1.443	0.423	0.319	0.298	0.347
100	1.737	1.163	1.035	1.312	0.411	0.280	0.252	0.314	100	1.749	1.265	1.156	1.390	0.413	0.304	0.281	0.332
Average	1.767	1.239	1.090	1.365	0.420	0.299	0.266	0.328	Average	1.777	1.328	1.199	1.435	0.421	0.320	0.293	0.345
Ind. IPC									*IPCP*								
20	1.794	1.308	1.121	1.408	0.427	0.318	0.274	0.339	20	1.793	1.394	1.229	1.472	0.427	0.339	0.300	0.355
50	1.753	1.224	1.097	1.358	0.415	0.295	0.270	0.327	50	1.792	1.326	1.213	1.444	0.423	0.319	0.298	0.347
100	1.704	1.155	1.031	1.297	0.403	0.278	0.251	0.310	100	1.749	1.266	1.156	1.390	0.413	0.304	0.281	0.333
Average	1.750	1.229	1.083	1.354	0.415	0.297	0.265	0.326	Average	1.778	1.329	1.200	1.435	0.421	0.321	0.293	0.345
Ind. PCX									*PCPX*								
20	2.195	1.460	1.197	1.617	0.523	0.353	0.292	0.389	20	1.808	1.398	1.230	1.479	0.431	0.339	0.301	0.357
50	2.163	1.392	1.182	1.579	0.513	0.334	0.290	0.379	50	1.797	1.328	1.213	1.446	0.425	0.320	0.298	0.348
100	2.148	1.333	1.120	1.534	0.508	0.319	0.271	0.366	100	1.752	1.266	1.156	1.392	0.414	0.304	0.281	0.333
Average	2.169	1.395	1.166	1.577	0.514	0.336	0.284	0.378	Average	1.786	1.331	1.200	1.439	0.423	0.321	0.293	0.346
Ind. PCX2S									*PCPX2S*								
20	1.848	1.322	1.126	1.432	0.440	0.321	0.275	0.345	20	1.793	1.393	1.228	1.471	0.427	0.338	0.300	0.355
50	1.809	1.236	1.101	1.382	0.429	0.297	0.271	0.332	50	1.791	1.325	1.212	1.443	0.423	0.319	0.298	0.347
100	1.767	1.166	1.035	1.323	0.418	0.280	0.251	0.317	100	1.749	1.265	1.156	1.390	0.413	0.304	0.281	0.333
Average	1.808	1.241	1.088	1.379	0.429	0.300	0.266	0.331	Average	1.778	1.328	1.199	1.435	0.421	0.320	0.293	0.345

Table A34: Forecasting Accuracy Measures, Low Heterogeneity – DGP4, Case f: Low Spatial Dependence & High Factor Dependence

	Heterogeneous									*Homogeneous*								
T	RMSE				Theil's U					RMSE				Theil's U				
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	3.188	2.885	2.794	2.956	0.758	0.714	0.666	0.712	20	3.286	3.112	3.059	3.152	0.778	0.768	0.727	0.758
50	3.158	2.900	2.809	2.956	0.749	0.686	0.638	0.691	50	3.255	3.129	3.084	3.156	0.769	0.739	0.699	0.736
100	3.167	2.870	2.778	2.938	0.722	0.671	0.650	0.681	100	3.276	3.102	3.046	3.141	0.744	0.723	0.711	0.726
Average	3.171	2.885	2.794	2.950	0.743	0.690	0.651	0.695	Average	3.273	3.114	3.063	3.150	0.764	0.743	0.712	0.740
Ind. GLS									*2WFE*								
20	3.099	2.865	2.789	2.918	0.735	0.708	0.664	0.702	20	3.881	3.821	3.865	3.856	0.920	0.948	0.926	0.931
50	3.061	2.880	2.804	2.915	0.724	0.681	0.637	0.680	50	3.853	3.877	3.882	3.871	0.911	0.919	0.887	0.906
100	3.063	2.849	2.771	2.894	0.696	0.665	0.648	0.670	100	3.893	3.857	3.829	3.860	0.884	0.903	0.896	0.894
Average	3.074	2.865	2.788	2.909	0.718	0.685	0.650	0.684	Average	3.876	3.852	3.859	3.862	0.905	0.923	0.903	0.911
Ind. CCE									*CCEP*								
20	1.810	1.263	1.133	1.402	0.435	0.319	0.280	0.345	20	1.829	1.348	1.234	1.470	0.438	0.340	0.304	0.361
50	1.737	1.221	1.094	1.351	0.415	0.296	0.256	0.322	50	1.761	1.317	1.206	1.428	0.420	0.319	0.282	0.340
100	1.744	1.161	1.073	1.326	0.401	0.278	0.259	0.313	100	1.764	1.266	1.190	1.406	0.404	0.303	0.287	0.331
Average	1.764	1.215	1.100	1.360	0.417	0.298	0.265	0.327	Average	1.785	1.310	1.210	1.435	0.421	0.321	0.291	0.344
Ind. CCEX									*CCEPX*								
20	1.827	1.270	1.136	1.411	0.439	0.321	0.280	0.347	20	1.829	1.348	1.234	1.470	0.438	0.340	0.304	0.361
50	1.745	1.224	1.096	1.355	0.417	0.297	0.256	0.323	50	1.761	1.317	1.206	1.428	0.420	0.319	0.282	0.340
100	1.748	1.163	1.074	1.328	0.402	0.278	0.259	0.313	100	1.764	1.266	1.190	1.406	0.404	0.303	0.287	0.331
Average	1.773	1.219	1.102	1.365	0.420	0.299	0.265	0.328	Average	1.785	1.310	1.210	1.435	0.421	0.321	0.291	0.344
Ind. IPC									*IPCP*								
20	1.821	1.257	1.127	1.402	0.437	0.318	0.278	0.344	20	1.831	1.349	1.235	1.472	0.438	0.341	0.305	0.361
50	1.718	1.214	1.090	1.341	0.411	0.294	0.255	0.320	50	1.761	1.317	1.207	1.428	0.420	0.319	0.282	0.340
100	1.718	1.155	1.070	1.314	0.395	0.276	0.258	0.310	100	1.764	1.266	1.190	1.407	0.404	0.303	0.287	0.331
Average	1.752	1.209	1.096	1.352	0.414	0.296	0.264	0.325	Average	1.785	1.311	1.211	1.436	0.421	0.321	0.291	0.344
Ind. PCX									*PCPX*								
20	2.201	1.442	1.210	1.618	0.528	0.363	0.298	0.396	20	1.843	1.355	1.236	1.478	0.442	0.342	0.305	0.363
50	2.121	1.385	1.175	1.560	0.507	0.335	0.274	0.372	50	1.767	1.319	1.207	1.431	0.421	0.320	0.282	0.341
100	2.141	1.331	1.156	1.542	0.492	0.318	0.278	0.362	100	1.767	1.267	1.190	1.408	0.405	0.303	0.287	0.332
Average	2.154	1.386	1.180	1.573	0.509	0.338	0.283	0.377	Average	1.792	1.314	1.211	1.439	0.423	0.322	0.291	0.345
Ind. PCX2S									*PCPX2S*								
20	1.874	1.276	1.132	1.427	0.450	0.322	0.279	0.350	20	1.830	1.347	1.233	1.470	0.438	0.340	0.304	0.361
50	1.772	1.226	1.094	1.364	0.424	0.297	0.256	0.325	50	1.761	1.317	1.206	1.428	0.420	0.319	0.282	0.340
100	1.776	1.165	1.073	1.338	0.409	0.279	0.259	0.316	100	1.764	1.266	1.190	1.406	0.405	0.303	0.287	0.331
Average	1.807	1.222	1.100	1.377	0.427	0.299	0.265	0.330	Average	1.785	1.310	1.210	1.435	0.421	0.321	0.291	0.344

Table A35: Forecasting Accuracy Measures, Low Heterogeneity – DGP4, Case h: High Spatial Dependence & High Factor Dependence

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	3.679	3.196	3.142	3.339	0.814	0.750	0.708	0.757	20	3.700	3.388	3.374	3.487	0.815	0.792	0.758	0.789
50	3.499	3.233	3.130	3.287	0.789	0.726	0.678	0.731	50	3.546	3.425	3.374	3.448	0.795	0.767	0.728	0.764
100	3.478	3.134	3.084	3.232	0.760	0.703	0.687	0.717	100	3.540	3.338	3.321	3.400	0.770	0.747	0.738	0.751
Average	3.552	3.188	3.119	3.286	0.788	0.726	0.691	0.735	Average	3.595	3.384	3.357	3.445	0.793	0.769	0.741	0.768
Ind. GLS									*2WFE*								
20	3.562	3.173	3.136	3.290	0.786	0.744	0.706	0.745	20	4.346	4.141	4.220	4.236	0.962	0.975	0.957	0.964
50	3.383	3.208	3.124	3.238	0.760	0.719	0.676	0.719	50	4.128	4.158	4.180	4.155	0.928	0.936	0.910	0.924
100	3.356	3.110	3.076	3.181	0.731	0.697	0.685	0.704	100	4.130	4.073	4.084	4.096	0.898	0.914	0.910	0.907
Average	3.434	3.164	3.112	3.236	0.759	0.720	0.689	0.723	Average	4.201	4.124	4.161	4.162	0.929	0.942	0.926	0.932
Ind. CCE									*CCEP*								
20	2.625	1.873	1.808	2.102	0.588	0.448	0.420	0.485	20	2.576	1.921	1.871	2.123	0.575	0.460	0.434	0.490
50	2.364	1.879	1.747	1.997	0.539	0.430	0.387	0.452	50	2.300	1.924	1.812	2.012	0.523	0.440	0.401	0.455
100	2.339	1.721	1.706	1.922	0.516	0.395	0.390	0.434	100	2.259	1.774	1.775	1.936	0.497	0.407	0.405	0.436
Average	2.443	1.825	1.754	2.007	0.548	0.424	0.399	0.457	Average	2.379	1.873	1.819	2.024	0.532	0.435	0.414	0.460
Ind. CCEX									*CCEPX*								
20	2.712	1.893	1.816	2.140	0.607	0.453	0.421	0.494	20	2.576	1.921	1.871	2.123	0.575	0.460	0.434	0.490
50	2.399	1.888	1.751	2.013	0.547	0.432	0.388	0.456	50	2.300	1.924	1.812	2.012	0.523	0.440	0.401	0.455
100	2.358	1.726	1.709	1.931	0.521	0.396	0.390	0.436	100	2.259	1.774	1.775	1.936	0.497	0.407	0.405	0.436
Average	2.490	1.836	1.758	2.028	0.558	0.427	0.400	0.462	Average	2.379	1.873	1.819	2.024	0.532	0.435	0.414	0.460
Ind. IPC									*IPCP*								
20	2.590	1.873	1.814	2.092	0.579	0.448	0.421	0.483	20	2.577	1.922	1.873	2.124	0.575	0.460	0.434	0.490
50	2.316	1.877	1.754	1.982	0.528	0.429	0.388	0.449	50	2.300	1.924	1.813	2.012	0.523	0.440	0.401	0.455
100	2.281	1.716	1.708	1.902	0.503	0.393	0.390	0.429	100	2.259	1.774	1.775	1.936	0.497	0.407	0.405	0.436
Average	2.396	1.822	1.758	1.992	0.537	0.424	0.400	0.453	Average	2.379	1.873	1.820	2.024	0.532	0.436	0.414	0.460
Ind. PCX									*PCPX*								
20	2.990	2.021	1.867	2.293	0.668	0.483	0.433	0.528	20	2.589	1.926	1.873	2.130	0.578	0.461	0.434	0.491
50	2.686	2.003	1.804	2.164	0.611	0.458	0.399	0.490	50	2.306	1.925	1.813	2.015	0.524	0.441	0.401	0.455
100	2.663	1.847	1.763	2.091	0.587	0.423	0.402	0.471	100	2.262	1.775	1.775	1.937	0.498	0.407	0.405	0.437
Average	2.780	1.957	1.811	2.183	0.622	0.454	0.411	0.496	Average	2.386	1.876	1.820	2.027	0.533	0.436	0.414	0.461
Ind. PCX2S									*PCPX2S*								
20	2.687	1.884	1.808	2.126	0.601	0.451	0.419	0.490	20	2.577	1.920	1.871	2.123	0.575	0.460	0.434	0.490
50	2.403	1.882	1.746	2.011	0.548	0.431	0.387	0.455	50	2.301	1.924	1.812	2.012	0.523	0.440	0.401	0.455
100	2.376	1.725	1.707	1.936	0.524	0.395	0.390	0.437	100	2.260	1.774	1.775	1.936	0.497	0.407	0.405	0.436
Average	2.489	1.830	1.754	2.024	0.558	0.426	0.399	0.461	Average	2.379	1.873	1.819	2.024	0.532	0.435	0.413	0.460

Table A36: Forecasting Accuracy Measures, High Heterogeneity – DGP1: No CSD

Heterogeneous

N \ T	RMSE 20	RMSE 50	RMSE 100	RMSE Average	Theil's U 20	Theil's U 50	Theil's U 100	Theil's U Average
Ind. OLS								
20	1.090	1.083	1.010	1.061	0.435	0.417	0.380	0.411
50	1.138	0.993	0.981	1.038	0.427	0.390	0.377	0.398
100	1.115	1.038	0.979	1.044	0.419	0.382	0.389	0.396
Average	1.114	1.038	0.990	1.048	0.427	0.396	0.382	0.402
Ind. GLS								
20	1.068	1.080	1.009	1.053	0.427	0.416	0.380	0.408
50	1.111	0.991	0.981	1.028	0.416	0.389	0.377	0.394
100	1.090	1.036	0.978	1.035	0.409	0.381	0.388	0.393
Average	1.090	1.036	0.990	1.038	0.418	0.395	0.382	0.398
Ind. CCE								
20	1.166	1.118	1.027	1.104	0.466	0.431	0.387	0.428
50	1.211	1.026	0.998	1.078	0.455	0.403	0.384	0.414
100	1.182	1.075	0.995	1.084	0.444	0.395	0.395	0.411
Average	1.186	1.073	1.007	1.089	0.455	0.410	0.388	0.418
Ind. CCEX								
20	1.172	1.119	1.027	1.106	0.468	0.431	0.387	0.429
50	1.216	1.027	0.998	1.080	0.456	0.403	0.384	0.414
100	1.185	1.075	0.995	1.085	0.445	0.395	0.395	0.412
Average	1.191	1.074	1.007	1.090	0.457	0.410	0.388	0.418
Ind. IPC								
20	1.236	1.128	1.030	1.131	0.490	0.435	0.388	0.438
50	1.230	1.029	0.998	1.086	0.461	0.404	0.384	0.416
100	1.186	1.075	0.995	1.085	0.446	0.395	0.395	0.412
Average	1.217	1.077	1.008	1.101	0.466	0.411	0.389	0.422
Ind. PCX								
20	1.194	1.123	1.029	1.115	0.476	0.433	0.387	0.432
50	1.242	1.030	0.999	1.091	0.466	0.405	0.384	0.418
100	1.213	1.079	0.996	1.096	0.456	0.397	0.396	0.416
Average	1.216	1.077	1.008	1.101	0.466	0.411	0.389	0.422
Ind. PCX2S								
20	1.225	1.128	1.030	1.128	0.488	0.435	0.388	0.437
50	1.271	1.034	1.000	1.102	0.477	0.406	0.385	0.423
100	1.238	1.081	0.997	1.106	0.465	0.398	0.396	0.420
Average	1.244	1.081	1.009	1.112	0.477	0.413	0.389	0.426

Homogeneous

	RMSE 20	RMSE 50	RMSE 100	RMSE Average	Theil's U 20	Theil's U 50	Theil's U 100	Theil's U Average
*FE**								
20	1.257	1.287	1.230	1.258	0.505	0.496	0.463	0.488
50	1.298	1.220	1.218	1.245	0.488	0.481	0.468	0.479
100	1.284	1.259	1.214	1.253	0.485	0.464	0.483	0.477
Average	1.280	1.255	1.221	1.252	0.492	0.480	0.471	0.481
2WFE								
20	1.401	1.420	1.398	1.406	0.561	0.546	0.522	0.543
50	1.402	1.346	1.396	1.381	0.525	0.529	0.530	0.528
100	1.375	1.380	1.336	1.364	0.517	0.507	0.529	0.518
Average	1.393	1.382	1.377	1.384	0.534	0.527	0.527	0.530
CCEP								
20	1.297	1.301	1.226	1.274	0.522	0.502	0.461	0.495
50	1.348	1.244	1.227	1.273	0.507	0.491	0.472	0.490
100	1.334	1.294	1.228	1.285	0.504	0.477	0.489	0.490
Average	1.326	1.279	1.227	1.278	0.511	0.490	0.474	0.492
CCEPX								
20	1.297	1.301	1.226	1.275	0.522	0.502	0.461	0.495
50	1.348	1.244	1.227	1.273	0.507	0.491	0.472	0.490
100	1.334	1.294	1.228	1.285	0.504	0.477	0.489	0.490
Average	1.326	1.279	1.227	1.278	0.511	0.490	0.474	0.492
IPCP								
20	1.299	1.302	1.227	1.276	0.523	0.503	0.462	0.496
50	1.348	1.244	1.227	1.273	0.507	0.491	0.472	0.490
100	1.334	1.294	1.228	1.285	0.504	0.477	0.489	0.490
Average	1.327	1.280	1.227	1.278	0.511	0.490	0.474	0.492
PCPX								
20	1.298	1.301	1.226	1.275	0.522	0.502	0.461	0.495
50	1.348	1.244	1.227	1.273	0.507	0.491	0.472	0.490
100	1.334	1.294	1.228	1.286	0.504	0.477	0.489	0.490
Average	1.327	1.280	1.227	1.278	0.511	0.490	0.474	0.492
PCPX2S								
20	1.299	1.301	1.227	1.276	0.523	0.502	0.461	0.495
50	1.349	1.244	1.227	1.273	0.507	0.491	0.472	0.490
100	1.335	1.294	1.228	1.286	0.505	0.477	0.489	0.490
Average	1.328	1.280	1.227	1.278	0.511	0.490	0.474	0.492

Table A37: Forecasting Accuracy Measures, High Heterogeneity – DGP2, Case a: Low Spatial Dependence

	Heterogeneous									*Homogeneous*							
	RMSE				Theil's U					RMSE				Theil's U			
N \ T	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	1.156	0.990	0.956	1.034	0.456	0.422	0.367	0.415	20	1.312	1.205	1.190	1.235	0.518	0.511	0.458	0.496
50	1.121	1.030	1.008	1.053	0.417	0.391	0.401	0.403	50	1.291	1.250	1.237	1.260	0.484	0.477	0.492	0.485
100	1.105	1.012	1.005	1.041	0.432	0.381	0.390	0.401	100	1.277	1.235	1.236	1.249	0.500	0.466	0.482	0.483
Average	1.127	1.011	0.990	1.043	0.435	0.398	0.386	0.406	Average	1.293	1.230	1.221	1.248	0.501	0.485	0.478	0.488
Ind. GLS									*2WFE*								
20	1.135	0.987	0.956	1.026	0.448	0.421	0.367	0.412	20	1.455	1.343	1.334	1.378	0.573	0.564	0.510	0.549
50	1.100	1.027	1.008	1.045	0.409	0.390	0.401	0.400	50	1.402	1.366	1.368	1.379	0.524	0.520	0.543	0.529
100	1.081	1.010	1.004	1.032	0.423	0.380	0.390	0.397	100	1.391	1.360	1.363	1.371	0.541	0.510	0.528	0.527
Average	1.105	1.008	0.989	1.034	0.427	0.397	0.386	0.403	Average	1.416	1.357	1.355	1.376	0.546	0.531	0.527	0.535
Ind. CCE									*CCEP*								
20	1.233	1.023	0.971	1.076	0.487	0.436	0.373	0.432	20	1.358	1.211	1.187	1.252	0.537	0.515	0.457	0.503
50	1.190	1.063	1.024	1.093	0.443	0.404	0.407	0.418	50	1.343	1.277	1.247	1.289	0.504	0.487	0.497	0.496
100	1.170	1.047	1.021	1.080	0.458	0.394	0.397	0.416	100	1.325	1.267	1.250	1.281	0.519	0.479	0.488	0.495
Average	1.198	1.044	1.006	1.083	0.463	0.411	0.392	0.422	Average	1.342	1.252	1.228	1.274	0.520	0.494	0.481	0.498
Ind. CCEX									*CCEPX*								
20	1.240	1.024	0.971	1.078	0.490	0.437	0.373	0.433	20	1.358	1.211	1.187	1.252	0.537	0.515	0.457	0.503
50	1.194	1.064	1.025	1.094	0.445	0.404	0.408	0.419	50	1.343	1.277	1.247	1.289	0.504	0.487	0.497	0.496
100	1.174	1.048	1.021	1.081	0.459	0.394	0.397	0.417	100	1.325	1.267	1.250	1.281	0.519	0.479	0.488	0.495
Average	1.203	1.045	1.006	1.085	0.465	0.412	0.392	0.423	Average	1.342	1.252	1.228	1.274	0.520	0.494	0.481	0.498
Ind. IPC									*IPCP*								
20	1.279	1.028	0.973	1.094	0.506	0.439	0.374	0.440	20	1.360	1.212	1.187	1.253	0.538	0.515	0.458	0.504
50	1.205	1.065	1.025	1.098	0.448	0.404	0.408	0.420	50	1.343	1.277	1.247	1.289	0.504	0.488	0.497	0.496
100	1.173	1.048	1.021	1.081	0.459	0.394	0.397	0.417	100	1.325	1.267	1.250	1.281	0.519	0.479	0.488	0.495
Average	1.219	1.047	1.007	1.091	0.471	0.413	0.393	0.426	Average	1.343	1.252	1.228	1.274	0.520	0.494	0.481	0.498
Ind. PCX									*PCPX*								
20	1.261	1.028	0.973	1.087	0.499	0.439	0.373	0.437	20	1.358	1.211	1.187	1.252	0.537	0.515	0.457	0.503
50	1.216	1.068	1.026	1.103	0.453	0.405	0.408	0.422	50	1.343	1.277	1.247	1.289	0.504	0.488	0.497	0.496
100	1.202	1.052	1.023	1.092	0.471	0.396	0.398	0.421	100	1.325	1.267	1.250	1.281	0.519	0.479	0.488	0.495
Average	1.226	1.049	1.007	1.094	0.474	0.413	0.393	0.427	Average	1.342	1.252	1.228	1.274	0.520	0.494	0.481	0.498
Ind. PCX2S									*PCPX2S*								
20	1.288	1.031	0.974	1.098	0.510	0.440	0.374	0.441	20	1.360	1.212	1.187	1.253	0.538	0.515	0.457	0.503
50	1.240	1.071	1.027	1.112	0.462	0.407	0.408	0.426	50	1.343	1.277	1.247	1.289	0.504	0.488	0.497	0.496
100	1.227	1.055	1.023	1.102	0.480	0.397	0.398	0.425	100	1.326	1.267	1.250	1.281	0.519	0.479	0.488	0.495
Average	1.252	1.052	1.008	1.104	0.484	0.414	0.393	0.431	Average	1.343	1.252	1.228	1.274	0.521	0.494	0.481	0.498

Table A38: Forecasting Accuracy Measures, High Heterogeneity – DGP2, Case b: High Spatial Dependence

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	2.154	1.919	1.680	1.918	0.690	0.646	0.547	0.628	20	2.138	2.013	1.820	1.990	0.684	0.676	0.592	0.651
50	1.858	1.690	1.653	1.734	0.606	0.557	0.565	0.576	50	1.887	1.815	1.799	1.833	0.616	0.598	0.615	0.610
100	1.780	1.596	1.604	1.660	0.607	0.533	0.544	0.561	100	1.816	1.731	1.755	1.767	0.618	0.578	0.596	0.598
Average	1.931	1.735	1.645	1.770	0.634	0.578	0.552	0.588	Average	1.947	1.853	1.791	1.864	0.639	0.617	0.601	0.619
Ind. GLS									*2WFE*								
20	2.075	1.907	1.678	1.887	0.664	0.641	0.546	0.617	20	2.467	2.389	2.151	2.336	0.793	0.805	0.702	0.767
50	1.794	1.681	1.652	1.709	0.584	0.553	0.564	0.567	50	2.043	1.995	1.999	2.012	0.668	0.658	0.684	0.670
100	1.713	1.588	1.602	1.635	0.583	0.530	0.544	0.552	100	1.932	1.870	1.909	1.904	0.656	0.624	0.648	0.643
Average	1.861	1.726	1.644	1.743	0.610	0.575	0.551	0.579	Average	2.147	2.085	2.020	2.084	0.706	0.696	0.678	0.693
Ind. CCE									*CCEP*								
20	2.227	1.964	1.701	1.964	0.715	0.661	0.554	0.643	20	2.247	2.064	1.835	2.048	0.720	0.694	0.598	0.671
50	1.946	1.738	1.677	1.787	0.635	0.573	0.574	0.594	50	1.977	1.865	1.822	1.888	0.647	0.615	0.623	0.628
100	1.869	1.649	1.628	1.716	0.638	0.551	0.553	0.581	100	1.895	1.785	1.780	1.820	0.646	0.597	0.605	0.616
Average	2.014	1.784	1.669	1.822	0.663	0.595	0.560	0.606	Average	2.039	1.905	1.812	1.919	0.671	0.636	0.609	0.638
Ind. CCEX									*CCEPX*								
20	2.312	1.987	1.708	2.002	0.743	0.669	0.556	0.656	20	2.247	2.064	1.835	2.049	0.721	0.694	0.598	0.671
50	1.979	1.746	1.681	1.802	0.646	0.576	0.575	0.599	50	1.977	1.865	1.822	1.888	0.647	0.615	0.623	0.628
100	1.891	1.654	1.630	1.725	0.646	0.552	0.554	0.584	100	1.895	1.785	1.780	1.820	0.646	0.597	0.606	0.616
Average	2.060	1.796	1.673	1.843	0.678	0.599	0.562	0.613	Average	2.040	1.905	1.812	1.919	0.671	0.636	0.609	0.638
Ind. IPC									*IPCP*								
20	2.197	1.956	1.699	1.951	0.705	0.659	0.553	0.639	20	2.245	2.064	1.834	2.048	0.720	0.694	0.598	0.670
50	1.914	1.732	1.675	1.774	0.625	0.571	0.573	0.590	50	1.976	1.865	1.822	1.888	0.646	0.615	0.623	0.628
100	1.840	1.644	1.627	1.704	0.628	0.549	0.553	0.577	100	1.894	1.785	1.780	1.820	0.646	0.597	0.605	0.616
Average	1.984	1.778	1.667	1.809	0.653	0.593	0.560	0.602	Average	2.039	1.905	1.812	1.918	0.671	0.636	0.609	0.638
Ind. PCX									*PCPX*								
20	2.349	1.996	1.710	2.019	0.755	0.672	0.557	0.661	20	2.251	2.065	1.835	2.050	0.722	0.694	0.598	0.671
50	2.016	1.752	1.683	1.817	0.659	0.577	0.576	0.604	50	1.978	1.866	1.822	1.888	0.647	0.616	0.623	0.629
100	1.936	1.660	1.632	1.743	0.661	0.555	0.554	0.590	100	1.895	1.785	1.780	1.820	0.646	0.597	0.606	0.616
Average	2.100	1.803	1.675	1.859	0.692	0.601	0.562	0.619	Average	2.041	1.905	1.812	1.920	0.672	0.636	0.609	0.639
Ind. PCX2S									*PCPX2S*								
20	2.254	1.964	1.701	1.973	0.724	0.661	0.554	0.646	20	2.247	2.064	1.834	2.048	0.721	0.694	0.598	0.671
50	1.983	1.740	1.677	1.800	0.649	0.574	0.574	0.599	50	1.977	1.865	1.822	1.888	0.647	0.615	0.623	0.629
100	1.932	1.655	1.630	1.739	0.660	0.553	0.554	0.589	100	1.895	1.785	1.780	1.820	0.646	0.597	0.605	0.616
Average	2.056	1.786	1.670	1.837	0.678	0.596	0.560	0.611	Average	2.040	1.905	1.812	1.919	0.671	0.636	0.609	0.639

Table A39: Forecasting Accuracy Measures, High Heterogeneity – DGP3, Case *c*: Low Factor Dependence

	Heterogeneous									*Homogeneous*							
T / N	RMSE				Theil's U					RMSE				Theil's U			
	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	1.885	1.771	1.664	1.773	0.562	0.526	0.497	0.528	20	2.169	2.104	2.032	2.102	0.646	0.623	0.606	0.625
50	1.912	1.762	1.695	1.789	0.558	0.519	0.506	0.528	50	2.202	2.119	2.072	2.131	0.640	0.623	0.616	0.627
100	1.906	1.729	1.670	1.768	0.559	0.509	0.493	0.520	100	2.189	2.094	2.055	2.113	0.640	0.614	0.605	0.620
Average	1.901	1.754	1.677	1.777	0.560	0.518	0.499	0.526	Average	2.187	2.106	2.053	2.115	0.642	0.620	0.609	0.624
Ind. GLS									*2WFE*								
20	1.848	1.765	1.663	1.758	0.551	0.524	0.497	0.524	20	2.487	2.480	2.458	2.475	0.737	0.728	0.728	0.731
50	1.871	1.755	1.693	1.773	0.546	0.517	0.506	0.523	50	2.524	2.465	2.464	2.484	0.729	0.722	0.730	0.727
100	1.860	1.722	1.669	1.750	0.545	0.507	0.492	0.514	100	2.491	2.476	2.439	2.469	0.722	0.720	0.714	0.719
Average	1.860	1.747	1.675	1.761	0.547	0.516	0.498	0.520	Average	2.501	2.473	2.453	2.476	0.729	0.723	0.724	0.726
Ind. CCE									*CCEP*								
20	1.393	1.179	1.036	1.203	0.417	0.357	0.313	0.362	20	1.544	1.374	1.251	1.390	0.463	0.415	0.379	0.419
50	1.411	1.128	1.053	1.197	0.416	0.337	0.319	0.358	50	1.564	1.343	1.279	1.395	0.459	0.401	0.387	0.416
100	1.407	1.074	1.000	1.160	0.414	0.320	0.299	0.345	100	1.554	1.303	1.239	1.365	0.457	0.388	0.371	0.405
Average	1.404	1.127	1.030	1.187	0.416	0.338	0.311	0.355	Average	1.554	1.340	1.256	1.384	0.459	0.401	0.379	0.413
Ind. CCEX									*CCEPX*								
20	1.399	1.180	1.036	1.205	0.419	0.357	0.313	0.363	20	1.544	1.374	1.252	1.390	0.463	0.415	0.379	0.419
50	1.413	1.128	1.053	1.198	0.417	0.337	0.320	0.358	50	1.564	1.343	1.279	1.395	0.459	0.401	0.387	0.416
100	1.408	1.074	1.000	1.161	0.415	0.320	0.299	0.345	100	1.554	1.303	1.239	1.365	0.457	0.388	0.371	0.405
Average	1.407	1.127	1.030	1.188	0.417	0.338	0.311	0.355	Average	1.554	1.340	1.256	1.384	0.459	0.401	0.379	0.413
Ind. IPC									*IPCP*								
20	1.414	1.177	1.033	1.208	0.423	0.357	0.312	0.364	20	1.547	1.376	1.254	1.392	0.463	0.415	0.379	0.419
50	1.395	1.123	1.050	1.189	0.411	0.335	0.318	0.355	50	1.566	1.344	1.280	1.397	0.459	0.401	0.387	0.416
100	1.375	1.067	0.997	1.146	0.405	0.319	0.298	0.341	100	1.555	1.304	1.239	1.366	0.457	0.388	0.371	0.405
Average	1.394	1.122	1.027	1.181	0.413	0.337	0.310	0.353	Average	1.556	1.341	1.258	1.385	0.460	0.402	0.379	0.413
Ind. PCX									*PCPX*								
20	1.552	1.225	1.056	1.278	0.464	0.370	0.319	0.384	20	1.548	1.375	1.251	1.391	0.464	0.415	0.379	0.419
50	1.551	1.179	1.077	1.269	0.457	0.352	0.326	0.378	50	1.566	1.344	1.279	1.396	0.459	0.401	0.387	0.416
100	1.551	1.128	1.025	1.235	0.456	0.336	0.307	0.366	100	1.555	1.304	1.239	1.366	0.457	0.389	0.371	0.406
Average	1.551	1.177	1.053	1.260	0.459	0.353	0.317	0.376	Average	1.556	1.341	1.256	1.384	0.460	0.402	0.379	0.414
Ind. PCX2S									*PCPX2S*								
20	1.452	1.184	1.035	1.224	0.434	0.359	0.313	0.368	20	1.545	1.374	1.251	1.390	0.463	0.415	0.379	0.419
50	1.445	1.131	1.053	1.210	0.426	0.338	0.319	0.361	50	1.565	1.343	1.278	1.396	0.459	0.401	0.387	0.416
100	1.433	1.076	1.000	1.170	0.422	0.321	0.299	0.348	100	1.554	1.303	1.239	1.365	0.457	0.388	0.371	0.405
Average	1.443	1.131	1.029	1.201	0.428	0.339	0.310	0.359	Average	1.555	1.340	1.256	1.384	0.460	0.401	0.379	0.413

Table A40: Forecasting Accuracy Measures, High Heterogeneity – DGP3, Case d: High Factor Dependence

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	3.154	2.899	2.762	2.938	0.744	0.681	0.654	0.693	20	3.356	3.206	3.113	3.225	0.789	0.750	0.735	0.758
50	3.188	2.912	2.793	2.964	0.744	0.680	0.661	0.695	50	3.404	3.241	3.159	3.268	0.790	0.755	0.745	0.763
100	3.171	2.884	2.781	2.945	0.742	0.674	0.653	0.690	100	3.364	3.215	3.150	3.243	0.783	0.748	0.738	0.756
Average	3.171	2.898	2.778	2.949	0.743	0.678	0.656	0.692	Average	3.375	3.221	3.141	3.245	0.787	0.751	0.739	0.759
Ind. GLS									*2WFE*								
20	3.073	2.883	2.758	2.905	0.723	0.676	0.653	0.684	20	3.990	3.983	3.966	3.980	0.937	0.932	0.938	0.935
50	3.103	2.895	2.788	2.929	0.722	0.676	0.659	0.686	50	4.045	3.981	3.956	3.994	0.940	0.931	0.936	0.935
100	3.074	2.866	2.776	2.905	0.717	0.669	0.652	0.679	100	3.982	4.007	3.944	3.977	0.927	0.932	0.926	0.929
Average	3.084	2.881	2.774	2.913	0.721	0.673	0.654	0.683	Average	4.006	3.990	3.955	3.984	0.935	0.931	0.933	0.933
Ind. CCE									*CCEP*								
20	1.773	1.314	1.129	1.405	0.421	0.318	0.274	0.338	20	1.892	1.490	1.327	1.570	0.449	0.360	0.323	0.377
50	1.770	1.232	1.102	1.368	0.417	0.295	0.269	0.327	50	1.897	1.431	1.318	1.549	0.445	0.343	0.321	0.370
100	1.734	1.162	1.035	1.310	0.408	0.278	0.250	0.312	100	1.857	1.377	1.267	1.500	0.436	0.329	0.306	0.357
Average	1.759	1.236	1.089	1.361	0.415	0.297	0.265	0.326	Average	1.882	1.433	1.304	1.540	0.443	0.344	0.317	0.368
Ind. CCEX									*CCEPX*								
20	1.789	1.319	1.131	1.413	0.425	0.319	0.275	0.340	20	1.892	1.490	1.327	1.570	0.449	0.360	0.323	0.377
50	1.776	1.234	1.103	1.371	0.419	0.295	0.270	0.328	50	1.897	1.431	1.318	1.549	0.445	0.343	0.321	0.370
100	1.737	1.163	1.035	1.312	0.409	0.278	0.251	0.313	100	1.857	1.377	1.267	1.500	0.436	0.329	0.306	0.357
Average	1.767	1.239	1.090	1.365	0.418	0.298	0.265	0.327	Average	1.882	1.433	1.304	1.540	0.443	0.344	0.317	0.368
Ind. IPC									*IPCP*								
20	1.794	1.308	1.121	1.408	0.425	0.316	0.273	0.338	20	1.894	1.492	1.329	1.572	0.449	0.360	0.323	0.377
50	1.753	1.224	1.097	1.358	0.413	0.293	0.268	0.325	50	1.898	1.432	1.320	1.550	0.445	0.343	0.322	0.370
100	1.704	1.155	1.031	1.297	0.401	0.276	0.250	0.309	100	1.857	1.378	1.268	1.501	0.436	0.329	0.307	0.357
Average	1.750	1.229	1.083	1.354	0.413	0.295	0.263	0.324	Average	1.883	1.434	1.306	1.541	0.443	0.344	0.317	0.368
Ind. PCX									*PCPX*								
20	2.195	1.460	1.197	1.617	0.520	0.352	0.291	0.388	20	1.907	1.494	1.329	1.577	0.453	0.361	0.323	0.379
50	2.163	1.392	1.182	1.579	0.510	0.332	0.288	0.377	50	1.902	1.434	1.319	1.551	0.446	0.343	0.322	0.370
100	2.148	1.333	1.120	1.534	0.506	0.318	0.270	0.365	100	1.860	1.378	1.267	1.502	0.437	0.329	0.307	0.357
Average	2.169	1.395	1.166	1.577	0.512	0.334	0.283	0.376	Average	1.890	1.435	1.305	1.543	0.445	0.344	0.317	0.369
Ind. PCX2S									*PCPX2S*								
20	1.848	1.322	1.126	1.432	0.438	0.320	0.274	0.344	20	1.894	1.490	1.326	1.570	0.449	0.359	0.322	0.377
50	1.809	1.236	1.101	1.382	0.426	0.296	0.269	0.330	50	1.897	1.431	1.318	1.549	0.445	0.343	0.321	0.370
100	1.767	1.166	1.035	1.323	0.416	0.279	0.250	0.315	100	1.857	1.377	1.267	1.500	0.436	0.329	0.306	0.357
Average	1.808	1.241	1.088	1.379	0.427	0.298	0.264	0.330	Average	1.883	1.433	1.304	1.540	0.443	0.344	0.317	0.368

Table A41: Forecasting Accuracy Measures, High Heterogeneity – DGP4, Case f: Low Spatial Dependence & High Factor Dependence

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	3.188	2.885	2.794	2.956	0.754	0.709	0.661	0.708	20	3.383	3.204	3.151	3.246	0.797	0.784	0.742	0.774
50	3.158	2.900	2.809	2.956	0.744	0.682	0.635	0.687	50	3.355	3.226	3.177	3.253	0.786	0.756	0.716	0.753
100	3.167	2.870	2.778	2.938	0.719	0.667	0.646	0.678	100	3.378	3.199	3.141	3.239	0.763	0.741	0.728	0.744
Average	3.171	2.885	2.794	2.950	0.739	0.686	0.647	0.691	Average	3.372	3.210	3.156	3.246	0.782	0.760	0.729	0.757
Ind. GLS									*2WFE*								
20	3.110	2.868	2.790	2.923	0.734	0.704	0.660	0.699	20	3.995	3.914	3.960	3.956	0.941	0.962	0.939	0.947
50	3.071	2.883	2.805	2.919	0.722	0.677	0.634	0.678	50	3.963	3.986	3.985	3.978	0.929	0.936	0.905	0.923
100	3.073	2.852	2.772	2.899	0.696	0.663	0.645	0.668	100	4.004	3.963	3.934	3.967	0.903	0.921	0.914	0.913
Average	3.085	2.868	2.789	2.914	0.717	0.681	0.646	0.682	Average	3.987	3.954	3.960	3.967	0.924	0.940	0.919	0.928
Ind. CCE									*CCEP*								
20	1.812	1.264	1.134	1.403	0.434	0.317	0.278	0.343	20	1.929	1.448	1.333	1.570	0.460	0.363	0.326	0.383
50	1.737	1.222	1.095	1.351	0.413	0.294	0.255	0.321	50	1.869	1.424	1.312	1.535	0.442	0.343	0.305	0.363
100	1.744	1.162	1.073	1.326	0.400	0.277	0.258	0.311	100	1.873	1.378	1.298	1.516	0.427	0.328	0.311	0.355
Average	1.765	1.216	1.101	1.360	0.416	0.296	0.263	0.325	Average	1.890	1.417	1.315	1.540	0.443	0.345	0.314	0.367
Ind. CCEX									*CCEPX*								
20	1.827	1.270	1.136	1.411	0.437	0.319	0.279	0.345	20	1.929	1.448	1.333	1.570	0.460	0.363	0.326	0.383
50	1.745	1.224	1.096	1.355	0.415	0.295	0.255	0.322	50	1.869	1.424	1.312	1.535	0.442	0.343	0.305	0.363
100	1.748	1.163	1.074	1.328	0.401	0.277	0.258	0.312	100	1.873	1.378	1.298	1.516	0.427	0.328	0.311	0.355
Average	1.773	1.219	1.102	1.365	0.418	0.297	0.264	0.326	Average	1.890	1.417	1.315	1.540	0.443	0.345	0.314	0.367
Ind. IPC									*IPCP*								
20	1.821	1.257	1.127	1.402	0.435	0.316	0.276	0.342	20	1.932	1.451	1.336	1.573	0.460	0.364	0.326	0.384
50	1.718	1.214	1.090	1.341	0.408	0.293	0.254	0.318	50	1.870	1.425	1.313	1.536	0.443	0.343	0.305	0.364
100	1.718	1.155	1.070	1.314	0.394	0.275	0.257	0.309	100	1.873	1.378	1.299	1.517	0.428	0.328	0.311	0.356
Average	1.752	1.209	1.096	1.352	0.412	0.294	0.262	0.323	Average	1.892	1.418	1.316	1.542	0.443	0.345	0.314	0.368
Ind. PCX									*PCPX*								
20	2.201	1.442	1.210	1.618	0.525	0.361	0.296	0.394	20	1.942	1.455	1.335	1.577	0.463	0.365	0.326	0.385
50	2.121	1.385	1.175	1.560	0.504	0.333	0.273	0.370	50	1.875	1.426	1.313	1.538	0.444	0.343	0.305	0.364
100	2.141	1.331	1.156	1.542	0.490	0.316	0.277	0.361	100	1.876	1.379	1.299	1.518	0.428	0.328	0.311	0.356
Average	2.154	1.386	1.180	1.573	0.506	0.337	0.282	0.375	Average	1.897	1.420	1.315	1.544	0.445	0.345	0.314	0.368
Ind. PCX2S									*PCPX2S*								
20	1.874	1.276	1.132	1.427	0.448	0.320	0.277	0.348	20	1.930	1.448	1.332	1.570	0.460	0.363	0.326	0.383
50	1.772	1.226	1.094	1.364	0.421	0.295	0.255	0.324	50	1.869	1.424	1.312	1.535	0.442	0.343	0.305	0.363
100	1.776	1.165	1.073	1.338	0.407	0.278	0.258	0.314	100	1.873	1.378	1.298	1.517	0.428	0.328	0.311	0.355
Average	1.807	1.222	1.100	1.377	0.426	0.298	0.263	0.329	Average	1.891	1.417	1.314	1.541	0.443	0.345	0.314	0.367

Table A42: Forecasting Accuracy Measures, High Heterogeneity – DGP4, Case h: High Spatial Dependence & High Factor Dependence

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	3.679	3.196	3.142	3.339	0.810	0.744	0.703	0.752	20	3.788	3.474	3.458	3.573	0.830	0.805	0.769	0.802
50	3.499	3.233	3.130	3.287	0.784	0.721	0.674	0.726	50	3.638	3.514	3.460	3.538	0.810	0.781	0.742	0.777
100	3.478	3.134	3.084	3.232	0.756	0.699	0.683	0.713	100	3.635	3.428	3.409	3.491	0.786	0.762	0.752	0.766
Average	3.552	3.188	3.119	3.286	0.783	0.722	0.687	0.731	Average	3.687	3.472	3.442	3.534	0.808	0.782	0.754	0.782
Ind. GLS									*2WFE*								
20	3.575	3.176	3.137	3.296	0.785	0.739	0.701	0.742	20	4.449	4.227	4.308	4.328	0.978	0.985	0.967	0.976
50	3.396	3.211	3.125	3.244	0.758	0.715	0.672	0.715	50	4.230	4.260	4.276	4.255	0.942	0.950	0.924	0.939
100	3.368	3.114	3.077	3.186	0.730	0.694	0.681	0.702	100	4.235	4.174	4.183	4.198	0.915	0.929	0.924	0.923
Average	3.446	3.167	3.113	3.242	0.758	0.716	0.685	0.720	Average	4.305	4.220	4.256	4.260	0.945	0.955	0.938	0.946
Ind. CCE									*CCEP*								
20	2.626	1.874	1.809	2.103	0.585	0.445	0.417	0.482	20	2.650	1.996	1.942	2.196	0.588	0.474	0.446	0.503
50	2.364	1.879	1.747	1.997	0.536	0.427	0.385	0.449	50	2.386	2.003	1.888	2.092	0.538	0.455	0.416	0.470
100	2.340	1.721	1.706	1.922	0.514	0.393	0.388	0.432	100	2.348	1.859	1.854	2.020	0.514	0.423	0.421	0.453
Average	2.443	1.825	1.754	2.007	0.545	0.422	0.396	0.454	Average	2.461	1.952	1.895	2.103	0.547	0.451	0.428	0.475
Ind. CCEX									*CCEPX*								
20	2.712	1.893	1.816	2.140	0.605	0.450	0.418	0.491	20	2.650	1.996	1.942	2.196	0.588	0.474	0.446	0.503
50	2.399	1.888	1.751	2.013	0.544	0.429	0.386	0.453	50	2.386	2.003	1.888	2.092	0.538	0.455	0.416	0.470
100	2.358	1.726	1.709	1.931	0.518	0.394	0.388	0.433	100	2.348	1.859	1.854	2.020	0.514	0.424	0.421	0.453
Average	2.490	1.836	1.758	2.028	0.556	0.424	0.397	0.459	Average	2.461	1.952	1.895	2.103	0.547	0.451	0.428	0.475
Ind. IPC									*IPCP*								
20	2.590	1.873	1.814	2.092	0.576	0.445	0.418	0.480	20	2.652	1.998	1.944	2.198	0.589	0.474	0.447	0.503
50	2.316	1.877	1.754	1.982	0.525	0.427	0.387	0.446	50	2.386	2.003	1.889	2.093	0.538	0.455	0.416	0.470
100	2.281	1.716	1.708	1.902	0.501	0.391	0.388	0.427	100	2.348	1.860	1.854	2.021	0.514	0.424	0.421	0.453
Average	2.396	1.822	1.758	1.992	0.534	0.421	0.397	0.451	Average	2.462	1.954	1.896	2.104	0.547	0.451	0.428	0.475
Ind. PCX									*PCPX*								
20	2.990	2.021	1.867	2.293	0.665	0.479	0.430	0.525	20	2.662	2.001	1.943	2.202	0.591	0.475	0.447	0.504
50	2.686	2.003	1.804	2.164	0.608	0.455	0.397	0.487	50	2.391	2.004	1.889	2.095	0.539	0.455	0.416	0.470
100	2.663	1.847	1.763	2.091	0.584	0.421	0.400	0.468	100	2.350	1.860	1.854	2.021	0.514	0.424	0.421	0.453
Average	2.780	1.957	1.811	2.183	0.619	0.452	0.409	0.493	Average	2.468	1.955	1.895	2.106	0.548	0.451	0.428	0.476
Ind. PCX2S									*PCPX2S*								
20	2.687	1.884	1.808	2.126	0.598	0.448	0.416	0.487	20	2.651	1.995	1.941	2.196	0.588	0.474	0.446	0.503
50	2.403	1.882	1.746	2.011	0.544	0.428	0.385	0.452	50	2.386	2.003	1.888	2.092	0.538	0.455	0.416	0.470
100	2.376	1.725	1.707	1.936	0.522	0.393	0.388	0.434	100	2.348	1.859	1.854	2.020	0.514	0.424	0.421	0.453
Average	2.489	1.830	1.754	2.024	0.555	0.423	0.396	0.458	Average	2.462	1.952	1.894	2.103	0.547	0.451	0.428	0.475

Table A43: Low Heterogeneity – DGP2, Case a: Low Spatial Dependence – SMA Errors

	Heterogeneous									Homogeneous							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	-0.06	-0.14	-0.32	0.17	11.16	9.42	8.89	9.82	20	0.13	-0.17	-0.29	0.19	11.42	9.86	9.08	10.12
50	-0.18	0.19	-0.20	0.19	6.94	5.85	5.54	6.11	50	-0.18	0.19	-0.21	0.19	7.19	6.08	5.77	6.35
100	-0.18	-0.11	0.11	0.13	5.02	4.17	4.09	4.43	100	-0.16	-0.15	0.08	0.13	5.12	4.38	4.17	4.56
Average	0.14	0.14	0.21	0.16	7.70	6.48	6.18	6.79	Average	0.15	0.17	0.19	0.17	7.91	6.77	6.34	7.01
*SW**									*2WFE*								
20	0.07	-0.13	-0.31	0.17	10.89	9.39	8.89	9.72	20	0.40	0.11	-0.27	0.26	13.34	11.20	9.99	11.51
50	-0.19	0.19	-0.20	0.19	6.71	5.84	5.54	6.03	50	-0.20	0.24	-0.31	0.25	7.68	7.21	7.07	7.32
100	-0.17	-0.11	0.11	0.13	4.85	4.16	4.09	4.37	100	-0.14	-0.09	0.07	0.10	5.37	5.08	4.72	5.06
Average	0.14	0.14	0.21	0.16	7.48	6.47	6.17	6.71	Average	0.25	0.15	0.22	0.20	8.80	7.83	7.26	7.96
CCEMG									*CCEP*								
20	0.14	-0.12	-0.29	0.18	12.05	9.50	8.91	10.15	20	0.22	-0.14	-0.28	0.22	12.01	9.94	9.10	10.35
50	-0.14	0.16	-0.21	0.17	7.44	5.90	5.56	6.30	50	-0.14	0.21	-0.21	0.19	7.53	6.14	5.79	6.48
100	-0.10	-0.12	0.11	0.11	5.34	4.22	4.11	4.56	100	-0.14	-0.16	0.08	0.13	5.34	4.40	4.20	4.65
Average	0.13	0.13	0.20	0.16	8.28	6.54	6.19	7.00	Average	0.17	0.17	0.19	0.18	8.29	6.83	6.36	7.16
CCEMGX									*CCEPX*								
20	0.26	-0.09	-0.30	0.22	12.15	9.53	8.89	10.19	20	0.32	-0.14	-0.27	0.25	12.05	9.95	9.08	10.36
50	-0.17	0.18	-0.22	0.19	7.44	5.91	5.55	6.30	50	-0.14	0.20	-0.21	0.19	7.56	6.14	5.78	6.49
100	-0.13	-0.12	0.10	0.12	5.43	4.22	4.11	4.59	100	-0.13	-0.15	0.08	0.12	5.37	4.42	4.20	4.66
Average	0.19	0.13	0.21	0.17	8.34	6.56	6.18	7.03	Average	0.20	0.17	0.19	0.18	8.33	6.83	6.36	7.17
IPCMG									*IPCP*								
20	0.01	-0.11	-0.34	0.15	13.77	9.85	9.05	10.89	20	0.01	-0.24	-0.40	0.21	12.85	10.49	9.64	10.99
50	-0.27	0.20	-0.19	0.22	7.93	5.96	5.59	6.49	50	-0.01	0.21	-0.20	0.14	7.64	6.34	5.94	6.64
100	-0.17	-0.09	0.11	0.12	5.43	4.23	4.10	4.59	100	-0.16	-0.16	0.08	0.13	5.41	4.45	4.24	4.70
Average	0.15	0.13	0.21	0.16	9.04	6.68	6.24	7.32	Average	0.06	0.20	0.23	0.16	8.63	7.09	6.61	7.44
PCMGX									*PCPX*								
20	-0.04	-0.18	-0.32	0.18	12.65	9.59	8.96	10.40	20	0.02	-0.26	-0.26	0.18	12.40	10.05	9.22	10.56
50	-0.17	0.19	-0.19	0.18	7.69	5.97	5.57	6.41	50	-0.07	0.19	-0.22	0.16	7.67	6.24	5.82	6.57
100	-0.24	-0.15	0.10	0.16	5.70	4.31	4.10	4.70	100	-0.26	-0.17	0.10	0.18	5.62	4.46	4.21	4.76
Average	0.15	0.17	0.21	0.18	8.68	6.62	6.21	7.17	Average	0.12	0.21	0.19	0.17	8.56	6.92	6.42	7.30
PCMGX2S									*PCPX2S*								
20	0.02	-0.19	-0.34	0.18	13.35	9.63	8.99	10.66	20	0.03	-0.22	-0.35	0.20	13.16	10.42	9.49	11.02
50	-0.20	0.19	-0.20	0.20	8.26	6.04	5.59	6.63	50	0.03	0.18	-0.22	0.14	8.04	6.41	5.95	6.80
100	-0.22	-0.13	0.10	0.15	6.01	4.35	4.10	4.82	100	-0.25	-0.16	0.08	0.17	5.90	4.54	4.26	4.90
Average	0.15	0.17	0.21	0.18	9.20	6.67	6.23	7.37	Average	0.11	0.19	0.22	0.17	9.03	7.12	6.56	7.57
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	5.65	6.40	6.55	6.20	14.85	17.45	18.15	16.82	20	6.40	6.95	6.25	6.53	13.25	16.35	18.40	16.00
50	5.20	5.50	4.60	5.10	29.35	39.60	41.45	36.80	50	5.35	5.25	5.30	5.30	28.55	36.65	37.40	34.20
100	4.85	5.00	5.90	5.25	50.65	65.10	68.05	61.27	100	5.15	5.50	5.50	5.38	48.20	59.10	65.65	57.65
Average	5.23	5.63	5.68	5.52	31.62	40.72	42.55	38.29	Average	5.63	5.90	5.68	5.74	30.00	37.37	40.48	35.95
*SW**									*2WFE*								
20	6.60	6.95	6.70	6.75	14.35	16.95	17.05	16.12	20	40.25	55.95	64.80	53.67	12.90	14.70	15.95	14.52
50	5.65	5.25	4.70	5.20	30.70	40.15	41.70	37.52	50	38.10	55.50	72.05	55.22	24.80	29.20	29.00	27.67
100	5.80	5.15	5.95	5.63	53.55	65.20	67.75	62.17	100	37.05	56.60	66.55	53.40	44.80	47.70	56.85	49.78
Average	6.02	5.78	5.78	5.86	32.87	40.77	42.17	38.60	Average	38.47	56.02	67.80	54.09	27.50	30.53	33.93	30.66
CCEMG									*CCEP*								
20	7.25	7.75	7.60	7.53	12.50	16.45	17.20	15.38	20	7.30	8.85	8.05	8.07	11.85	15.90	18.65	15.47
50	6.25	5.95	4.90	5.70	25.50	37.60	42.40	35.17	50	6.70	5.90	5.90	6.17	23.60	34.85	37.15	31.87
100	5.10	5.05	6.15	5.43	46.75	63.85	68.45	59.68	100	5.25	5.70	5.65	5.53	45.80	58.55	66.60	56.98
Average	6.20	6.25	6.22	6.22	28.25	39.30	42.68	36.74	Average	6.42	6.82	6.53	6.59	27.08	36.43	40.80	34.77
CCEMGX									*CCEPX*								
20	6.60	6.55	6.00	6.38	11.95	17.00	18.00	15.65	20	6.05	6.85	6.15	6.35	13.05	15.50	18.65	15.73
50	5.25	5.40	4.35	5.00	26.10	39.00	41.85	35.65	50	6.75	5.05	5.60	5.80	22.50	36.70	36.65	31.95
100	5.20	5.00	5.75	5.32	44.80	63.95	67.75	58.83	100	4.90	5.25	5.35	5.17	46.30	58.95	66.15	57.13
Average	5.68	5.65	5.37	5.57	27.62	39.98	42.53	36.71	Average	5.90	5.72	5.70	5.77	27.28	37.05	40.48	34.94
IPCMG									*IPCP*								
20	4.95	6.50	6.20	5.88	13.55	16.40	18.10	16.02	20	7.35	9.95	8.45	8.58	12.05	16.00	17.60	15.22
50	5.40	5.85	5.30	5.52	24.55	38.40	39.75	34.23	50	6.25	7.45	6.95	6.88	27.75	34.90	37.40	33.35
100	5.35	4.50	5.50	5.12	44.00	66.20	68.75	59.65	100	6.60	6.50	6.45	6.52	43.25	57.75	66.25	55.75
Average	5.23	5.62	5.67	5.51	27.37	40.33	42.20	36.63	Average	6.73	7.97	7.28	7.33	27.68	36.22	40.42	34.77
PCMGX									*PCPX*								
20	6.10	6.80	6.75	6.55	11.15	15.80	18.50	15.15	20	6.75	6.65	6.15	6.52	12.10	15.55	17.65	15.10
50	5.20	5.15	4.55	4.97	25.35	38.75	41.85	35.32	50	5.60	4.85	5.30	5.25	26.15	37.45	37.65	33.75
100	4.75	4.95	5.50	5.07	43.30	62.70	68.70	58.23	100	5.35	4.70	5.30	5.12	41.90	58.95	66.80	55.88
Average	5.35	5.63	5.60	5.53	26.60	39.08	43.02	36.23	Average	5.90	5.40	5.58	5.63	26.72	37.32	40.70	34.91
PCMGX2S									*PCPX2S*								
20	6.20	6.30	6.55	6.35	11.00	15.95	18.35	15.10	20	8.40	8.50	7.50	8.13	10.60	16.10	18.70	15.13
50	5.45	5.45	4.70	5.20	22.10	37.10	40.60	33.27	50	6.85	7.10	6.50	6.82	25.20	36.50	38.35	33.35
100	4.90	4.65	5.10	4.88	38.60	62.70	69.75	57.02	100	6.50	5.45	6.20	6.05	38.30	57.20	66.55	54.02
Average	5.52	5.47	5.45	5.48	23.90	38.58	42.90	35.13	Average	7.25	7.02	6.73	7.00	24.70	36.60	41.20	34.17

Table A44: Low Heterogeneity – DGP2, Case *b*: High Spatial Dependence – SMA Errors

	Heterogeneous									*Homogeneous*							
	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	-0.09	-0.14	-0.36	0.19	11.63	9.54	8.97	10.04	20	0.14	-0.17	-0.32	0.21	11.73	9.96	9.14	10.28
50	-0.22	0.18	-0.21	0.20	7.16	5.94	5.58	6.23	50	-0.19	0.19	-0.21	0.20	7.37	6.17	5.81	6.45
100	-0.18	-0.12	0.12	0.14	5.17	4.23	4.11	4.50	100	-0.16	-0.16	0.09	0.14	5.25	4.42	4.19	4.62
Average	0.16	0.14	0.23	0.18	7.99	6.57	6.22	6.92	Average	0.16	0.17	0.21	0.18	8.11	6.85	6.38	7.11
*SW**									*2WFE*								
20	0.04	-0.13	-0.35	0.17	11.29	9.51	8.97	9.92	20	0.42	0.12	-0.29	0.27	13.57	11.22	9.99	11.59
50	-0.21	0.19	-0.22	0.20	6.93	5.93	5.58	6.15	50	-0.20	0.25	-0.31	0.25	7.76	7.24	7.09	7.36
100	-0.15	-0.12	0.12	0.13	5.01	4.21	4.10	4.44	100	-0.13	-0.10	0.07	0.10	5.41	5.09	4.73	5.08
Average	0.14	0.15	0.23	0.17	7.74	6.55	6.22	6.84	Average	0.25	0.16	0.23	0.21	8.91	7.85	7.27	8.01
CCEMG									*CCEP*								
20	0.14	-0.11	-0.31	0.19	12.43	9.58	8.96	10.32	20	0.27	-0.15	-0.30	0.24	12.30	10.01	9.13	10.48
50	-0.20	0.16	-0.23	0.19	7.71	6.00	5.60	6.43	50	-0.18	0.21	-0.22	0.20	7.72	6.22	5.83	6.59
100	-0.11	-0.13	0.12	0.12	5.54	4.26	4.13	4.65	100	-0.14	-0.17	0.09	0.13	5.48	4.44	4.22	4.71
Average	0.15	0.13	0.22	0.17	8.56	6.62	6.23	7.13	Average	0.20	0.18	0.20	0.19	8.50	6.89	6.39	7.26
CCEMGX									*CCEPX*								
20	0.22	-0.07	-0.32	0.21	12.63	9.63	8.94	10.40	20	0.36	-0.14	-0.29	0.26	12.32	10.02	9.12	10.48
50	-0.24	0.18	-0.23	0.22	7.68	6.01	5.58	6.43	50	-0.18	0.21	-0.22	0.20	7.73	6.22	5.82	6.59
100	-0.15	-0.13	0.11	0.13	5.64	4.28	4.13	4.68	100	-0.12	-0.16	0.09	0.12	5.51	4.46	4.22	4.73
Average	0.20	0.13	0.22	0.18	8.65	6.64	6.22	7.17	Average	0.22	0.17	0.20	0.20	8.52	6.90	6.38	7.27
IPCMG									*IPCP*								
20	-0.11	-0.15	-0.33	0.20	12.53	9.51	8.95	10.33	20	-0.03	-0.20	-0.33	0.19	12.41	10.10	9.29	10.60
50	-0.11	0.18	-0.22	0.17	7.69	5.98	5.60	6.42	50	-0.11	0.19	-0.24	0.18	7.60	6.27	5.87	6.58
100	-0.16	-0.11	0.12	0.13	5.45	4.28	4.12	4.62	100	-0.16	-0.15	0.09	0.13	5.44	4.46	4.22	4.70
Average	0.13	0.15	0.22	0.16	8.56	6.59	6.22	7.12	Average	0.10	0.18	0.22	0.17	8.48	6.94	6.46	7.30
PCMGX									*PCPX*								
20	-0.13	-0.18	-0.36	0.22	13.34	9.77	9.06	10.72	20	0.01	-0.26	-0.28	0.19	12.90	10.17	9.30	10.79
50	-0.21	0.20	-0.20	0.20	8.01	6.09	5.62	6.57	50	-0.09	0.20	-0.22	0.17	7.87	6.34	5.86	6.69
100	-0.25	-0.17	0.12	0.18	5.94	4.39	4.12	4.81	100	-0.26	-0.18	0.11	0.18	5.79	4.53	4.23	4.85
Average	0.19	0.18	0.23	0.20	9.10	6.75	6.27	7.37	Average	0.12	0.21	0.21	0.18	8.85	7.01	6.46	7.44
PCMGX2S									*PCPX2S*								
20	-0.06	-0.22	-0.33	0.20	13.67	9.63	8.99	10.76	20	-0.05	-0.25	-0.30	0.20	13.07	10.23	9.30	10.87
50	-0.12	0.17	-0.22	0.17	8.43	6.13	5.62	6.73	50	0.00	0.19	-0.26	0.15	8.05	6.39	5.91	6.78
100	-0.21	-0.17	0.11	0.16	6.16	4.42	4.13	4.91	100	-0.24	-0.18	0.09	0.17	5.93	4.57	4.25	4.91
Average	0.13	0.19	0.22	0.18	9.42	6.73	6.25	7.46	Average	0.10	0.21	0.22	0.17	9.02	7.06	6.49	7.52

	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	5.50	6.65	6.75	6.30	14.00	17.55	16.90	16.15	20	6.40	6.75	6.55	6.57	12.80	15.95	17.20	15.32
50	4.95	5.55	4.90	5.13	29.70	37.90	40.85	36.15	50	5.75	5.40	5.45	5.53	27.35	36.00	37.25	33.53
100	5.00	5.05	5.45	5.17	47.45	63.70	68.35	59.83	100	5.15	5.50	5.15	5.27	47.65	57.70	66.00	57.12
Average	5.15	5.75	5.70	5.53	30.38	39.72	42.03	37.38	Average	5.77	5.88	5.72	5.79	29.27	36.55	40.15	35.32
*SW**									*2WFE*								
20	6.35	7.35	6.70	6.80	14.45	17.25	16.80	16.17	20	39.25	54.55	63.65	52.48	12.80	14.90	16.00	14.57
50	6.25	5.45	4.95	5.55	29.55	38.55	40.20	36.10	50	37.10	53.55	70.65	53.77	25.25	29.40	28.85	27.83
100	5.45	5.30	5.40	5.38	51.20	64.10	68.40	61.23	100	35.50	54.80	65.20	51.83	44.25	47.85	56.35	49.48
Average	6.02	6.03	5.68	5.91	31.73	39.97	41.80	37.83	Average	37.28	54.30	66.50	52.69	27.43	30.72	33.73	30.63
CCEMG									*CCEP*								
20	7.35	8.55	7.55	7.82	11.70	16.85	17.35	15.30	20	7.55	8.70	7.60	7.95	12.50	16.30	17.90	15.57
50	6.10	5.85	5.30	5.75	25.40	36.15	40.25	33.93	50	6.30	6.10	5.85	6.08	23.70	34.00	36.90	31.53
100	5.25	5.15	5.85	5.42	43.50	63.10	67.45	58.02	100	5.40	5.45	5.35	5.40	43.60	57.65	66.85	56.03
Average	6.23	6.52	6.23	6.33	26.87	38.70	41.68	35.75	Average	6.42	6.75	6.27	6.48	26.60	35.98	40.55	34.38
CCEMGX									*CCEPX*								
20	5.85	6.85	5.80	6.17	11.20	17.15	18.10	15.48	20	5.95	6.80	6.00	6.25	12.20	15.75	17.55	15.17
50	4.95	5.70	4.70	5.12	25.90	36.25	40.65	34.27	50	6.80	5.30	5.45	5.85	21.15	35.70	36.60	31.15
100	5.10	5.15	5.65	5.30	43.00	62.30	67.30	57.53	100	5.35	5.70	4.90	5.32	42.35	57.05	67.35	55.58
Average	5.30	5.90	5.38	5.53	26.70	38.57	42.02	35.76	Average	6.03	5.93	5.45	5.81	25.23	36.17	40.50	33.97
IPCMG									*IPCP*								
20	5.15	6.35	6.45	5.98	14.70	17.00	17.90	16.53	20	7.65	7.85	7.40	7.63	12.50	16.40	17.60	15.50
50	4.70	5.25	5.00	4.98	27.20	38.30	39.95	35.15	50	6.25	6.65	6.20	6.37	26.25	34.35	36.90	32.50
100	4.70	4.95	5.85	5.17	44.15	63.60	67.45	58.40	100	5.75	5.80	5.85	5.80	43.55	59.00	65.45	56.00
Average	4.85	5.52	5.77	5.38	28.68	39.63	41.77	36.69	Average	6.55	6.77	6.48	6.60	27.43	36.58	39.98	34.67
PCMGX									*PCPX*								
20	5.65	7.10	6.30	6.35	11.60	16.15	17.55	15.10	20	5.95	7.30	5.90	6.38	12.05	15.75	18.50	15.43
50	5.00	4.95	4.80	4.92	23.95	39.10	40.65	34.57	50	5.50	5.25	5.25	5.33	24.05	36.30	37.35	32.57
100	4.70	5.10	5.30	5.03	38.95	60.90	69.00	56.28	100	5.80	4.80	5.00	5.20	40.90	58.30	67.30	55.50
Average	5.12	5.72	5.47	5.43	24.83	38.72	42.40	35.32	Average	5.75	5.78	5.38	5.64	25.67	36.78	41.05	34.50
PCMGX2S									*PCPX2S*								
20	5.55	6.10	6.40	6.02	11.60	16.50	18.10	15.40	20	7.60	6.95	6.65	7.07	10.95	15.10	17.15	14.40
50	6.00	5.45	4.85	5.43	21.25	37.30	40.45	33.00	50	6.35	6.25	5.85	6.15	23.75	35.85	37.55	32.38
100	5.45	5.00	5.40	5.28	33.90	59.70	68.60	54.07	100	5.70	5.45	5.35	5.50	37.10	56.65	66.55	53.43
Average	5.67	5.52	5.55	5.58	22.25	37.83	42.38	34.16	Average	6.55	6.22	5.95	6.24	23.93	35.87	40.42	33.41

Table A45: Low Heterogeneity – DGP4, Case e: Low Spatial Dependence & Low Factor Dependence – SMA Errors

	Heterogeneous									*Homogeneous*							
T / N	Bias (x 100) 20	50	100	Average	RMSE (x 100) 20	50	100	Average		Bias (x 100) 20	50	100	Average	RMSE (x 100) 20	50	100	Average
*MG**									*FE**								
20	17.81	18.18	17.13	17.71	23.47	22.54	20.65	22.22	20	21.38	22.61	21.76	21.92	27.14	27.04	25.59	26.59
50	18.70	17.73	17.36	17.93	22.08	19.68	18.99	20.25	50	22.38	22.52	22.13	22.34	26.03	24.74	23.96	24.91
100	17.92	17.82	17.65	17.80	20.14	19.06	18.62	19.27	100	22.10	22.44	22.60	22.38	24.85	23.87	23.74	24.15
Average	18.14	17.91	17.38	17.81	21.90	20.43	19.42	20.58	Average	21.95	22.52	22.16	22.21	26.01	25.22	24.43	25.22
*SW**									*2WFE*								
20	18.96	18.72	17.42	18.37	24.10	22.87	20.87	22.61	20	-0.25	0.18	-0.17	0.20	12.35	11.75	11.02	11.70
50	19.79	18.36	17.65	18.60	22.83	20.23	19.26	20.78	50	-0.01	-0.25	-0.21	0.16	8.17	7.14	7.02	7.44
100	19.17	18.40	17.99	18.52	21.30	19.59	18.94	19.94	100	-0.05	-0.21	0.09	0.12	5.50	5.09	5.08	5.22
Average	19.31	18.49	17.69	18.49	22.74	20.90	19.69	21.11	Average	0.10	0.21	0.16	0.16	8.67	7.99	7.70	8.12
CCEMG									*CCEP*								
20	-0.31	0.15	-0.20	0.22	11.48	9.57	8.99	10.01	20	-0.50	0.23	-0.19	0.31	11.95	10.24	9.45	10.55
50	0.33	-0.31	0.04	0.23	7.87	5.95	5.71	6.51	50	0.06	-0.22	0.00	0.09	7.73	6.20	5.89	6.60
100	-0.06	-0.18	0.09	0.11	5.27	4.30	3.99	4.52	100	-0.09	-0.25	0.10	0.15	5.36	4.48	4.16	4.67
Average	0.24	0.21	0.11	0.19	8.21	6.61	6.23	7.02	Average	0.22	0.23	0.10	0.18	8.35	6.97	6.50	7.27
CCEMGX									*CCEPX*								
20	-0.25	0.17	-0.20	0.21	11.61	9.61	8.99	10.07	20	-0.52	0.21	-0.18	0.30	11.98	10.24	9.45	10.55
50	0.31	-0.32	0.05	0.23	7.96	5.97	5.72	6.55	50	0.03	-0.22	0.01	0.09	7.76	6.19	5.89	6.62
100	-0.08	-0.19	0.09	0.12	5.28	4.31	4.00	4.53	100	-0.10	-0.25	0.09	0.15	5.36	4.48	4.16	4.67
Average	0.21	0.23	0.11	0.18	8.28	6.63	6.24	7.05	Average	0.22	0.23	0.10	0.18	8.36	6.97	6.50	7.28
IPCMG									*IPCP*								
20	-0.63	0.21	-0.20	0.35	12.35	9.65	8.98	10.33	20	-0.92	-0.48	-0.41	0.60	12.68	11.28	10.44	11.46
50	0.40	-0.26	0.05	0.24	7.78	5.89	5.66	6.45	50	-0.29	-0.58	-0.29	0.39	8.08	6.70	6.61	7.13
100	0.06	-0.16	0.09	0.10	5.03	4.20	3.96	4.40	100	-0.40	-0.45	-0.04	0.30	5.53	5.03	4.78	5.11
Average	0.36	0.21	0.11	0.23	8.39	6.58	6.20	7.06	Average	0.53	0.50	0.25	0.43	8.76	7.67	7.28	7.90
PCMGX									*PCPX*								
20	0.73	0.61	-0.13	0.49	14.71	11.10	9.39	11.73	20	0.49	0.49	-0.19	0.39	13.86	11.17	9.56	11.53
50	0.65	-0.09	0.13	0.29	10.10	6.76	5.99	7.62	50	0.39	-0.04	0.08	0.17	9.19	6.76	6.10	7.35
100	0.42	0.05	0.11	0.19	6.70	4.86	4.24	5.27	100	0.38	-0.04	0.12	0.18	6.38	4.86	4.34	5.20
Average	0.60	0.25	0.13	0.33	10.50	7.58	6.54	8.21	Average	0.42	0.19	0.13	0.25	9.81	7.60	6.67	8.02
PCMGX2S									*PCPX2S*								
20	-0.08	0.35	-0.19	0.21	12.70	9.81	8.93	10.48	20	-0.44	0.21	-0.25	0.30	12.52	10.34	9.25	10.70
50	0.33	-0.25	0.09	0.22	8.58	6.02	5.70	6.77	50	0.01	-0.25	-0.01	0.09	8.11	6.24	5.88	6.74
100	-0.01	-0.16	0.11	0.09	5.55	4.31	3.99	4.62	100	-0.07	-0.24	0.11	0.14	5.51	4.51	4.13	4.71
Average	0.14	0.25	0.13	0.17	8.94	6.71	6.21	7.29	Average	0.17	0.23	0.12	0.18	8.71	7.03	6.42	7.39
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	26.40	33.65	33.50	31.18	15.75	17.20	19.30	17.42	20	33.10	40.10	41.35	38.18	14.10	15.35	16.30	15.25
50	48.25	61.20	66.35	58.60	20.55	26.50	34.40	27.15	50	59.95	71.95	74.60	68.83	16.55	23.80	26.20	22.18
100	72.20	85.50	90.60	82.77	30.65	45.95	51.05	42.55	100	80.45	92.15	94.50	89.03	25.95	37.00	40.75	34.57
Average	48.95	60.12	63.48	57.52	22.32	29.88	34.92	29.04	Average	57.83	68.07	70.15	65.35	18.87	25.38	27.75	24.00
*SW**									*2WFE*								
20	30.25	35.65	35.00	33.63	16.00	16.50	18.90	17.13	20	41.65	60.00	70.40	57.35	12.50	12.75	14.05	13.10
50	56.30	64.40	67.50	62.73	21.70	27.10	34.20	27.67	50	39.90	58.95	68.95	55.93	24.15	28.25	29.00	27.13
100	79.95	88.25	91.90	86.70	30.25	47.00	50.35	42.53	100	40.55	60.10	72.35	57.67	43.45	47.15	51.10	47.23
Average	55.50	62.77	64.80	61.02	22.65	30.20	34.48	29.11	Average	40.70	59.68	70.57	56.98	26.70	29.38	31.38	29.16
CCEMG									*CCEP*								
20	6.60	7.60	7.95	7.38	13.40	16.75	17.00	15.72	20	7.30	7.75	8.10	7.72	12.35	16.45	15.70	14.83
50	6.05	6.35	6.35	6.25	22.90	34.80	40.30	32.67	50	5.75	5.85	6.45	6.02	25.10	33.60	38.25	32.32
100	4.95	6.55	4.75	5.42	47.25	60.10	71.05	59.47	100	5.20	6.00	5.50	5.57	45.35	58.65	66.15	56.72
Average	5.87	6.83	6.35	6.35	27.85	37.22	42.78	35.95	Average	6.08	6.53	6.68	6.43	27.60	36.23	40.03	34.62
CCEMGX									*CCEPX*								
20	5.10	6.00	6.90	6.00	13.65	15.95	16.40	15.33	20	5.65	6.65	6.85	6.38	12.65	16.40	15.55	14.87
50	6.10	5.40	6.00	5.83	22.95	35.00	39.95	32.63	50	5.15	5.30	5.95	5.47	25.80	33.05	38.35	32.40
100	4.70	6.50	4.65	5.28	47.00	59.95	71.15	59.37	100	5.05	5.65	5.30	5.33	45.15	58.25	66.95	56.78
Average	5.30	5.97	5.85	5.71	27.87	36.97	42.50	35.78	Average	5.28	5.87	6.03	5.73	27.87	35.90	40.28	34.68
IPCMG									*IPCP*								
20	6.30	6.40	6.75	6.48	11.45	15.70	17.60	14.92	20	7.85	10.05	9.55	9.15	10.10	13.75	14.40	12.75
50	5.70	5.40	5.65	5.58	25.60	36.10	41.10	34.27	50	7.15	6.25	7.75	7.05	23.70	28.25	29.45	27.13
100	4.95	5.65	4.65	5.08	51.50	63.75	72.60	62.62	100	5.85	7.80	7.00	6.88	42.75	45.45	55.50	47.90
Average	5.65	5.82	5.68	5.72	29.52	38.52	43.77	37.27	Average	6.95	8.03	8.10	7.69	25.52	29.15	33.12	29.26
PCMGX									*PCPX*								
20	6.10	6.05	6.25	6.13	11.25	16.40	15.65	14.43	20	5.50	6.10	6.20	5.93	12.10	15.40	16.35	14.62
50	5.30	5.40	5.15	5.28	18.05	28.00	37.65	27.90	50	5.35	4.75	5.05	5.05	18.75	29.90	37.65	28.77
100	5.45	5.60	4.65	5.23	33.65	53.00	66.15	50.93	100	4.85	5.60	5.35	5.27	38.00	50.25	61.70	49.98
Average	5.62	5.68	5.35	5.55	20.98	32.47	39.82	31.09	Average	5.23	5.48	5.53	5.42	22.95	31.85	38.57	31.12
PCMGX2S									*PCPX2S*								
20	5.85	6.40	6.45	6.23	11.35	16.80	17.15	15.10	20	6.85	7.00	7.25	7.03	10.85	16.75	16.10	14.57
50	5.65	5.30	6.20	5.72	21.60	34.70	40.50	32.27	50	5.60	5.45	6.45	5.83	22.95	34.40	37.00	31.45
100	4.90	6.05	4.50	5.15	43.60	59.10	70.80	57.83	100	5.30	5.55	5.30	5.38	43.35	57.40	67.40	56.05
Average	5.47	5.92	5.72	5.70	25.52	36.87	42.82	35.07	Average	5.92	6.00	6.33	6.08	25.72	36.18	40.17	34.02

Table A46: Low Heterogeneity – DGP4, Case f: Low Spatial Dependence & High Factor Dependence – SMA Errors

	Heterogeneous									*Homogeneous*							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	35.89	36.26	34.54	35.56	43.57	41.78	38.56	41.30	20	43.41	45.13	43.79	44.11	50.66	50.25	47.72	49.54
50	37.20	35.76	34.71	35.89	42.17	38.34	36.65	39.06	50	44.76	45.22	44.33	44.77	50.18	48.09	46.45	48.24
100	35.92	35.81	35.24	35.66	39.46	37.55	36.46	37.82	100	44.26	45.11	45.12	44.83	48.82	47.21	46.56	47.53
Average	36.33	35.94	34.83	35.70	41.73	39.22	37.22	39.39	Average	44.14	45.15	44.41	44.57	49.89	48.52	46.91	48.44
*SW**									*2WFE*								
20	38.97	37.79	35.44	37.40	45.86	42.93	39.32	42.70	20	-0.21	0.19	-0.16	0.19	12.92	12.24	11.54	12.23
50	40.00	37.44	35.62	37.69	44.50	39.91	37.51	40.64	50	-0.02	-0.26	-0.22	0.17	8.61	7.50	7.34	7.82
100	39.06	37.42	36.19	37.56	42.52	39.10	37.39	39.67	100	-0.07	-0.20	0.09	0.12	5.76	5.30	5.28	5.45
Average	39.34	37.55	35.75	37.55	44.29	40.65	38.07	41.00	Average	0.10	0.22	0.16	0.16	9.10	8.35	8.05	8.50
CCEMG									*CCEP*								
20	-0.34	0.14	-0.18	0.22	11.72	9.76	9.13	10.20	20	-0.52	0.24	-0.16	0.31	12.19	10.46	9.63	10.76
50	0.32	-0.31	0.05	0.22	7.93	6.00	5.74	6.56	50	0.06	-0.22	0.01	0.09	7.77	6.24	5.93	6.65
100	-0.06	-0.18	0.10	0.11	5.30	4.32	4.01	4.54	100	-0.09	-0.25	0.10	0.15	5.38	4.49	4.17	4.68
Average	0.24	0.21	0.11	0.19	8.32	6.69	6.29	7.10	Average	0.22	0.23	0.09	0.18	8.45	7.06	6.57	7.36
CCEMGX									*CCEPX*								
20	-0.25	0.20	-0.18	0.21	11.99	9.86	9.15	10.33	20	-0.51	0.21	-0.16	0.29	12.21	10.46	9.63	10.77
50	0.32	-0.32	0.05	0.23	8.05	6.03	5.76	6.61	50	0.04	-0.23	0.01	0.09	7.80	6.24	5.93	6.66
100	-0.08	-0.19	0.09	0.12	5.32	4.33	4.01	4.55	100	-0.10	-0.25	0.09	0.15	5.38	4.49	4.17	4.68
Average	0.21	0.24	0.11	0.19	8.45	6.74	6.31	7.17	Average	0.22	0.23	0.09	0.18	8.46	7.06	6.58	7.37
IPCMG									*IPCP*								
20	-0.74	0.21	-0.20	0.38	12.56	9.60	8.89	10.35	20	-0.52	-0.11	-0.26	0.30	12.36	11.25	10.53	11.38
50	0.22	-0.30	0.05	0.19	7.73	5.87	5.66	6.42	50	0.00	-0.35	-0.11	0.15	8.08	6.82	6.66	7.19
100	-0.04	-0.17	0.09	0.10	5.00	4.20	3.96	4.39	100	-0.13	-0.26	0.15	0.18	5.49	5.05	4.82	5.12
Average	0.33	0.22	0.11	0.22	8.43	6.55	6.17	7.05	Average	0.22	0.24	0.17	0.21	8.64	7.70	7.34	7.90
PCMGX									*PCPX*								
20	1.74	1.14	0.01	0.96	20.94	14.31	10.75	15.33	20	1.35	0.88	-0.14	0.79	18.57	13.63	10.77	14.32
50	1.16	0.11	0.21	0.50	14.37	8.64	6.78	9.93	50	0.83	0.15	0.13	0.37	12.11	8.26	6.80	9.06
100	0.90	0.27	0.13	0.43	9.60	6.10	4.86	6.85	100	0.81	0.13	0.14	0.36	8.64	5.86	4.87	6.45
Average	1.27	0.51	0.12	0.63	14.97	9.68	7.46	10.71	Average	0.99	0.39	0.14	0.51	13.11	9.25	7.48	9.94
PCMGX2S									*PCPX2S*								
20	-0.16	0.40	-0.15	0.24	13.39	10.08	8.98	10.82	20	-0.35	0.28	-0.23	0.29	12.60	10.33	9.21	10.71
50	0.18	-0.24	0.10	0.18	8.77	6.07	5.71	6.85	50	0.02	-0.24	0.01	0.09	8.14	6.24	5.87	6.75
100	-0.02	-0.16	0.11	0.09	5.63	4.31	3.99	4.64	100	-0.05	-0.24	0.11	0.13	5.50	4.50	4.13	4.71
Average	0.12	0.27	0.12	0.17	9.26	6.82	6.23	7.44	Average	0.14	0.25	0.12	0.17	8.75	7.02	6.40	7.39
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	38.95	50.95	55.25	48.38	9.80	10.55	12.35	10.90	20	52.25	64.25	68.20	61.57	10.50	10.55	11.30	10.78
50	67.10	84.70	90.65	80.82	11.40	16.95	16.90	15.08	50	83.10	93.30	95.55	90.65	12.10	14.05	15.55	13.90
100	87.30	98.55	99.35	95.07	19.00	28.35	30.10	25.82	100	93.70	99.80	99.95	97.82	14.45	21.50	21.60	19.18
Average	64.45	78.07	81.75	74.76	13.40	18.62	19.78	17.27	Average	76.35	85.78	87.90	83.34	12.35	15.37	16.15	14.62
*SW**									*2WFE*								
20	46.50	55.55	58.55	53.53	9.55	10.45	12.05	10.68	20	40.20	59.05	69.70	56.32	11.85	12.00	13.40	12.42
50	77.60	87.55	92.20	85.78	11.35	16.40	16.60	14.78	50	39.75	57.95	68.65	55.45	22.20	25.75	25.90	24.62
100	93.20	99.30	99.50	97.33	17.75	27.50	29.70	24.98	100	38.35	58.05	70.70	55.70	40.45	44.30	49.25	44.67
Average	72.43	80.80	83.42	78.88	12.88	18.12	19.45	16.82	Average	39.43	58.35	69.68	55.82	24.83	27.35	29.52	27.23
CCEMG									*CCEP*								
20	6.65	7.40	7.80	7.28	12.60	15.60	16.45	14.88	20	7.55	7.85	8.00	7.80	12.25	15.90	15.05	14.40
50	6.05	5.95	6.45	6.15	23.35	34.85	40.05	32.75	50	5.65	5.85	6.50	6.00	25.60	32.65	38.05	32.10
100	5.00	6.60	4.85	5.48	46.75	60.00	71.25	59.33	100	5.15	6.10	5.40	5.55	44.45	58.15	66.25	56.28
Average	5.90	6.65	6.37	6.31	27.57	36.82	42.58	35.66	Average	6.12	6.60	6.63	6.45	27.43	35.57	39.78	34.26
CCEMGX									*CCEPX*								
20	4.70	5.90	6.30	5.63	12.90	15.65	16.95	15.17	20	5.35	6.20	6.65	6.07	11.70	15.40	15.30	14.13
50	5.50	5.05	5.95	5.50	22.45	34.95	39.15	32.18	50	5.25	5.20	5.95	5.47	25.30	33.10	37.70	32.03
100	4.55	6.40	4.65	5.20	46.85	59.30	70.85	59.00	100	5.05	5.60	5.20	5.28	44.20	57.65	66.55	56.13
Average	4.92	5.78	5.63	5.44	27.40	36.63	42.32	35.45	Average	5.22	5.67	5.93	5.61	27.07	35.38	39.85	34.10
IPCMG									*IPCP*								
20	5.45	6.15	6.75	6.12	11.60	17.55	17.25	15.47	20	6.95	8.60	9.00	8.18	10.40	14.40	14.20	13.00
50	5.70	5.45	5.75	5.63	24.55	36.55	41.60	34.23	50	6.60	5.80	6.70	6.37	23.50	30.35	31.60	28.48
100	4.90	5.80	4.60	5.10	50.95	63.45	72.80	62.40	100	5.15	6.60	5.85	5.87	45.65	49.80	56.80	50.75
Average	5.35	5.80	5.70	5.62	29.03	39.18	43.88	37.37	Average	6.23	7.00	7.18	6.81	26.52	31.52	34.20	30.74
PCMGX									*PCPX*								
20	5.45	5.90	5.50	5.62	8.70	12.90	14.45	12.02	20	4.90	5.80	5.05	5.25	9.95	12.30	15.05	12.43
50	5.55	5.10	4.95	5.20	12.20	19.70	30.30	20.73	50	5.20	5.00	4.80	5.00	13.85	21.05	31.20	22.03
100	5.10	4.95	4.60	4.88	23.25	39.55	53.40	38.73	100	5.30	5.10	4.85	5.08	26.70	38.60	53.15	39.48
Average	5.37	5.32	5.02	5.23	14.72	24.05	32.72	23.83	Average	5.13	5.30	4.90	5.11	16.83	23.98	33.13	24.65
PCMGX2S									*PCPX2S*								
20	5.80	5.90	7.00	6.23	10.70	16.75	17.00	14.82	20	6.80	6.40	6.95	6.72	11.65	16.80	17.00	15.15
50	5.50	5.85	6.10	5.82	20.30	33.45	40.15	31.30	50	5.35	5.20	6.10	5.55	23.85	33.75	37.85	31.82
100	5.05	5.95	4.60	5.20	41.85	58.95	70.80	57.20	100	5.00	5.50	5.15	5.22	44.00	58.00	67.05	56.35
Average	5.45	5.90	5.90	5.75	24.28	36.38	42.65	34.44	Average	5.72	5.70	6.07	5.83	26.50	36.18	40.63	34.44

Table A47: Low Heterogeneity – DGP4, Case *g*: High Spatial Dependence & Low Factor Dependence – SMA Errors

	Heterogeneous									*Homogeneous*							
	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	17.79	18.22	17.13	17.71	23.60	22.62	20.67	22.30	20	21.39	22.64	21.77	21.93	27.26	27.10	25.61	26.66
50	18.68	17.72	17.34	17.92	22.14	19.70	18.98	20.27	50	22.40	22.52	22.12	22.35	26.06	24.75	23.96	24.92
100	17.92	17.82	17.65	17.80	20.18	19.08	18.62	19.29	100	22.09	22.44	22.60	22.38	24.87	23.88	23.74	24.16
Average	18.13	17.92	17.37	17.81	21.98	20.46	19.42	20.62	Average	21.96	22.53	22.17	22.22	26.06	25.24	24.44	25.25
*SW**									*2WFE*								
20	19.02	18.80	17.44	18.42	24.26	22.99	20.91	22.72	20	-0.21	0.22	-0.16	0.20	12.44	11.74	11.04	11.74
50	19.85	18.39	17.66	18.63	22.94	20.28	19.27	20.83	50	-0.01	-0.25	-0.22	0.16	8.20	7.17	7.02	7.46
100	19.22	18.43	18.01	18.55	21.39	19.64	18.96	20.00	100	-0.06	-0.20	0.10	0.12	5.55	5.10	5.08	5.24
Average	19.36	18.54	17.70	18.53	22.86	20.97	19.71	21.18	Average	0.09	0.23	0.16	0.16	8.73	8.00	7.72	8.15
CCEMG									*CCEP*								
20	-0.30	0.22	-0.23	0.25	11.76	9.68	9.02	10.15	20	-0.51	0.31	-0.20	0.34	12.10	10.28	9.48	10.62
50	0.32	-0.31	0.02	0.22	8.16	6.03	5.71	6.63	50	0.06	-0.21	-0.02	0.10	7.88	6.27	5.89	6.68
100	-0.04	-0.17	0.10	0.10	5.45	4.37	4.02	4.61	100	-0.07	-0.24	0.09	0.13	5.46	4.54	4.18	4.73
Average	0.22	0.23	0.11	0.19	8.46	6.69	6.25	7.13	Average	0.21	0.25	0.11	0.19	8.48	7.03	6.52	7.34
CCEMGX									*CCEPX*								
20	-0.22	0.25	-0.21	0.23	11.93	9.73	9.02	10.23	20	-0.55	0.29	-0.20	0.35	12.13	10.28	9.47	10.63
50	0.28	-0.31	0.03	0.21	8.29	6.04	5.72	6.68	50	0.03	-0.22	-0.01	0.09	7.91	6.27	5.90	6.69
100	-0.07	-0.18	0.09	0.12	5.47	4.37	4.02	4.62	100	-0.08	-0.25	0.09	0.14	5.46	4.53	4.18	4.72
Average	0.19	0.25	0.11	0.18	8.56	6.71	6.25	7.18	Average	0.22	0.25	0.10	0.19	8.50	7.02	6.52	7.35
IPCMG									*IPCP*								
20	-0.30	0.28	-0.24	0.27	11.93	9.69	9.09	10.23	20	-1.00	-0.64	-0.52	0.72	12.81	11.36	10.52	11.56
50	0.47	-0.23	0.02	0.24	7.94	5.99	5.69	6.54	50	-0.40	-0.64	-0.34	0.46	8.25	6.78	6.62	7.22
100	0.10	-0.15	0.08	0.11	5.16	4.26	3.99	4.47	100	-0.42	-0.46	-0.07	0.32	5.59	5.06	4.79	5.15
Average	0.29	0.22	0.11	0.21	8.34	6.65	6.25	7.08	Average	0.61	0.58	0.31	0.50	8.88	7.73	7.31	7.98
PCMGX									*PCPX*								
20	0.73	0.67	-0.14	0.51	15.19	11.25	9.43	11.96	20	0.47	0.56	-0.21	0.41	14.13	11.26	9.60	11.66
50	0.60	-0.08	0.11	0.26	10.40	6.85	5.99	7.75	50	0.36	-0.04	0.05	0.15	9.38	6.83	6.10	7.44
100	0.42	0.06	0.12	0.20	6.85	4.93	4.26	5.35	100	0.38	-0.03	0.12	0.18	6.45	4.92	4.36	5.25
Average	0.59	0.27	0.12	0.33	10.81	7.68	6.56	8.35	Average	0.40	0.21	0.13	0.25	9.99	7.67	6.68	8.12
PCMGX2S									*PCPX2S*								
20	-0.06	0.37	-0.21	0.21	12.88	9.91	8.96	10.58	20	-0.36	0.29	-0.24	0.29	12.64	10.36	9.28	10.76
50	0.35	-0.23	0.06	0.22	8.87	6.10	5.71	6.89	50	0.01	-0.26	-0.02	0.10	8.28	6.31	5.88	6.82
100	0.03	-0.15	0.11	0.10	5.76	4.38	4.01	4.71	100	-0.07	-0.24	0.10	0.13	5.64	4.58	4.15	4.79
Average	0.15	0.25	0.13	0.18	9.17	6.80	6.22	7.40	Average	0.14	0.26	0.12	0.18	8.85	7.09	6.44	7.46
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	25.90	33.35	33.95	31.07	15.30	16.50	18.90	16.90	20	32.45	40.15	41.25	37.95	13.20	15.40	16.40	15.00
50	47.60	59.85	65.75	57.73	20.70	26.70	34.35	27.25	50	59.55	71.75	74.35	68.55	16.55	23.40	26.55	22.17
100	71.35	85.05	90.50	82.30	30.10	45.75	51.20	42.35	100	80.20	92.25	94.45	88.97	25.05	36.60	41.55	34.40
Average	48.28	59.42	63.40	57.03	22.03	29.65	34.82	28.83	Average	57.40	68.05	70.02	65.16	18.27	25.13	28.17	23.86
*SW**									*2WFE*								
20	29.80	35.00	35.30	33.37	14.70	16.15	18.40	16.42	20	40.60	58.40	70.55	56.52	12.75	13.35	14.30	13.47
50	55.70	64.20	67.40	62.43	21.80	26.30	33.70	27.27	50	39.15	57.75	68.65	55.18	23.35	28.90	28.70	26.98
100	79.50	88.25	92.00	86.58	28.45	47.05	50.75	42.08	100	40.20	59.25	70.75	56.73	42.95	46.05	51.00	46.67
Average	55.00	62.48	64.90	60.79	21.65	29.83	34.28	28.59	Average	39.98	58.47	69.98	56.14	26.35	29.43	31.33	29.04
CCEMG									*CCEP*								
20	6.30	7.40	7.65	7.12	13.20	16.15	16.40	15.25	20	6.90	7.80	8.00	7.57	12.35	15.80	15.40	14.52
50	5.50	5.85	6.25	5.87	24.45	34.00	39.55	32.67	50	5.30	5.65	6.40	5.78	25.35	33.25	37.55	32.05
100	5.20	6.65	4.75	5.53	42.90	58.70	70.45	57.35	100	4.70	6.15	5.30	5.38	46.80	56.05	66.20	56.35
Average	5.67	6.63	6.22	6.17	26.85	36.28	42.13	35.09	Average	5.63	6.53	6.57	6.24	28.17	35.03	39.72	34.31
CCEMGX									*CCEPX*								
20	4.85	6.30	6.50	5.88	14.00	15.30	15.95	15.08	20	5.40	6.50	6.85	6.25	11.50	15.45	15.35	14.10
50	5.90	5.10	5.60	5.53	21.50	35.45	38.90	31.95	50	4.85	5.05	5.80	5.23	24.85	32.85	38.10	31.93
100	4.85	6.25	4.50	5.20	43.50	58.50	71.00	57.67	100	4.50	5.60	4.90	5.00	45.50	56.30	66.90	56.23
Average	5.20	5.88	5.53	5.54	26.33	36.42	41.95	34.90	Average	4.92	5.72	5.85	5.49	27.28	34.87	40.12	34.09
IPCMG									*IPCP*								
20	5.60	5.80	6.90	6.10	13.05	17.40	17.30	15.92	20	8.35	9.80	9.50	9.22	10.80	14.05	13.90	12.92
50	6.15	5.30	5.75	5.73	24.85	35.60	40.30	33.58	50	7.55	6.30	7.25	7.03	22.20	28.65	29.60	26.82
100	5.00	6.10	4.60	5.23	48.50	60.60	72.05	60.38	100	6.15	7.25	6.75	6.72	40.70	44.55	54.30	46.52
Average	5.58	5.73	5.75	5.69	28.80	37.87	43.22	36.63	Average	7.35	7.78	7.83	7.66	24.57	29.08	32.60	28.75
PCMGX									*PCPX*								
20	5.75	6.20	6.20	6.05	10.45	14.15	14.95	13.18	20	5.50	6.05	6.10	5.88	10.95	15.00	16.35	14.10
50	5.35	5.70	5.50	5.52	17.85	27.55	36.25	27.22	50	5.60	4.75	5.25	5.20	16.90	29.80	36.25	27.65
100	5.75	5.35	4.60	5.23	31.80	51.50	65.35	49.55	100	5.10	5.45	5.35	5.30	35.40	49.45	62.60	49.15
Average	5.62	5.75	5.43	5.60	20.03	31.07	38.85	29.98	Average	5.40	5.42	5.57	5.46	21.08	31.42	38.40	30.30
PCMGX2S									*PCPX2S*								
20	6.00	6.35	6.75	6.37	11.25	16.50	17.45	15.07	20	6.65	6.95	7.35	6.98	10.70	16.90	16.40	14.67
50	5.35	5.50	5.75	5.53	21.80	34.45	39.80	32.02	50	5.55	5.35	6.15	5.68	21.85	34.25	38.05	31.38
100	4.80	6.15	4.65	5.20	41.40	60.15	70.95	57.50	100	5.10	6.10	5.30	5.50	42.25	54.50	67.35	54.70
Average	5.38	6.00	5.72	5.70	24.82	37.03	42.73	34.86	Average	5.77	6.13	6.27	6.06	24.93	35.22	40.60	33.58

Table A48: Low Heterogeneity – DGP4, Case *h*: High Spatial Dependence & High Factor Dependence – SMA Errors

	Heterogeneous									*Homogeneous*							
T / *N*	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	35.87	36.30	34.54	35.57	43.64	41.83	38.57	41.35	20	43.42	45.16	43.79	44.12	50.72	50.29	47.73	49.58
50	37.18	35.75	34.70	35.88	42.20	38.35	36.64	39.06	50	44.77	45.21	44.32	44.77	50.19	48.10	46.45	48.25
100	35.92	35.81	35.24	35.66	39.48	37.56	36.46	37.83	100	44.26	45.12	45.11	44.83	48.82	47.22	46.56	47.53
Average	36.32	35.96	34.83	35.70	41.77	39.25	37.22	39.41	Average	44.15	45.16	44.41	44.57	49.91	48.54	46.91	48.45
*SW**									*2WFE*								
20	38.98	37.87	35.46	37.44	45.92	43.03	39.34	42.76	20	-0.17	0.23	-0.14	0.18	13.01	12.23	11.56	12.27
50	40.04	37.46	35.62	37.71	44.56	39.94	37.52	40.67	50	-0.03	-0.26	-0.23	0.17	8.64	7.52	7.35	7.84
100	39.09	37.45	36.21	37.58	42.57	39.14	37.41	39.71	100	-0.07	-0.20	0.09	0.12	5.81	5.32	5.29	5.47
Average	39.37	37.59	35.76	37.58	44.35	40.70	38.09	41.05	Average	0.09	0.23	0.15	0.16	9.15	8.36	8.07	8.53
CCEMG									*CCEP*								
20	-0.34	0.22	-0.20	0.25	11.97	9.86	9.16	10.33	20	-0.54	0.31	-0.17	0.34	12.34	10.50	9.65	10.83
50	0.30	-0.30	0.02	0.21	8.22	6.08	5.74	6.68	50	0.06	-0.22	-0.02	0.10	7.92	6.31	5.93	6.72
100	-0.04	-0.17	0.10	0.10	5.47	4.38	4.03	4.63	100	-0.07	-0.24	0.10	0.14	5.47	4.55	4.19	4.74
Average	0.23	0.23	0.10	0.19	8.55	6.77	6.31	7.21	Average	0.23	0.26	0.10	0.19	8.58	7.12	6.59	7.43
CCEMGX									*CCEPX*								
20	-0.22	0.28	-0.19	0.23	12.29	9.98	9.18	10.48	20	-0.54	0.28	-0.17	0.33	12.37	10.50	9.65	10.84
50	0.30	-0.31	0.03	0.21	8.38	6.11	5.76	6.75	50	0.04	-0.23	-0.01	0.09	7.95	6.31	5.93	6.73
100	-0.07	-0.18	0.09	0.11	5.51	4.39	4.03	4.64	100	-0.08	-0.24	0.09	0.14	5.48	4.55	4.19	4.74
Average	0.19	0.26	0.10	0.19	8.73	6.83	6.32	7.29	Average	0.22	0.25	0.09	0.19	8.60	7.12	6.59	7.44
IPCMG									*IPCP*								
20	-0.59	0.30	-0.24	0.38	12.54	9.73	9.00	10.42	20	-0.49	-0.09	-0.29	0.29	12.67	11.34	10.56	11.52
50	0.26	-0.29	0.02	0.19	8.02	5.97	5.67	6.55	50	-0.04	-0.37	-0.13	0.18	8.20	6.88	6.67	7.25
100	-0.03	-0.16	0.09	0.09	5.14	4.26	3.98	4.46	100	-0.14	-0.26	0.14	0.18	5.55	5.08	4.83	5.15
Average	0.29	0.25	0.12	0.22	8.57	6.65	6.22	7.15	Average	0.22	0.24	0.19	0.22	8.81	7.77	7.36	7.98
PCMGX									*PCPX*								
20	1.74	1.20	0.00	0.98	21.33	14.41	10.78	15.51	20	1.33	0.94	-0.16	0.81	18.78	13.71	10.80	14.43
50	1.10	0.12	0.19	0.47	14.59	8.71	6.78	10.03	50	0.80	0.15	0.11	0.35	12.27	8.32	6.80	9.13
100	0.90	0.28	0.14	0.44	9.70	6.16	4.88	6.91	100	0.81	0.13	0.14	0.36	8.68	5.91	4.88	6.49
Average	1.25	0.53	0.11	0.63	15.21	9.76	7.48	10.82	Average	0.98	0.41	0.13	0.51	13.25	9.31	7.49	10.02
PCMGX2S									*PCPX2S*								
20	-0.11	0.45	-0.17	0.25	13.67	10.19	9.01	10.96	20	-0.31	0.36	-0.24	0.30	12.80	10.38	9.25	10.81
50	0.22	-0.23	0.08	0.18	9.09	6.15	5.71	6.98	50	-0.01	-0.24	-0.01	0.09	8.30	6.32	5.87	6.83
100	0.01	-0.15	0.11	0.09	5.83	4.38	4.01	4.74	100	-0.04	-0.23	0.10	0.13	5.61	4.57	4.15	4.77
Average	0.12	0.28	0.12	0.17	9.53	6.91	6.24	7.56	Average	0.12	0.28	0.12	0.17	8.90	7.09	6.42	7.47
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	38.95	51.30	55.45	48.57	9.70	10.60	12.20	10.83	20	52.15	64.25	68.25	61.55	9.50	10.60	11.65	10.58
50	67.10	84.10	90.85	80.68	11.35	16.85	16.75	14.98	50	82.75	93.20	95.60	90.52	12.75	14.20	16.00	14.32
100	86.95	98.50	99.35	94.93	18.45	28.25	29.95	25.55	100	93.70	99.75	99.95	97.80	14.55	20.85	21.55	18.98
Average	64.33	77.97	81.88	74.73	13.17	18.57	19.63	17.12	Average	76.20	85.73	87.93	83.29	12.27	15.22	16.40	14.63
*SW**									*2WFE*								
20	46.05	55.30	58.50	53.28	10.15	10.30	12.20	10.88	20	39.80	57.75	69.45	55.67	12.05	12.25	13.30	12.53
50	77.20	87.45	92.20	85.62	11.55	16.20	16.50	14.75	50	38.50	56.60	67.90	54.33	22.85	25.75	26.10	24.90
100	93.00	99.30	99.50	97.27	17.30	27.30	29.40	24.67	100	37.70	56.35	70.00	54.68	39.65	44.80	49.20	44.55
Average	72.08	80.68	83.40	78.72	13.00	17.93	19.37	16.77	Average	38.67	56.90	69.12	54.89	24.85	27.60	29.53	27.33
CCEMG									*CCEP*								
20	5.90	7.30	7.65	6.95	13.00	15.40	16.35	14.92	20	7.00	7.85	8.20	7.68	11.25	14.75	15.25	13.75
50	5.60	6.00	6.25	5.95	23.40	34.40	39.30	32.37	50	5.40	5.70	6.50	5.87	24.25	32.80	37.70	31.58
100	5.05	6.75	4.85	5.55	42.85	58.70	69.90	57.15	100	4.75	6.10	5.35	5.40	46.05	55.55	66.20	55.93
Average	5.52	6.68	6.25	6.15	26.42	36.17	41.85	34.81	Average	5.72	6.55	6.68	6.32	27.18	34.37	39.72	33.76
CCEMGX									*CCEPX*								
20	4.60	5.90	6.45	5.65	12.60	15.35	16.20	14.72	20	5.00	5.95	6.60	5.85	11.80	15.75	14.80	14.12
50	5.60	4.90	5.65	5.38	21.40	35.00	38.45	31.62	50	4.70	5.05	5.80	5.18	24.05	32.70	37.05	31.27
100	4.80	6.35	4.55	5.23	43.05	58.45	69.70	57.07	100	4.35	5.55	5.10	5.00	44.75	56.30	66.30	55.78
Average	5.00	5.72	5.55	5.42	25.68	36.27	41.45	34.47	Average	4.68	5.52	5.83	5.34	26.87	34.92	39.38	33.72
IPCMG									*IPCP*								
20	5.55	5.90	6.95	6.13	12.70	16.15	16.80	15.22	20	6.80	8.55	8.40	7.92	11.45	14.15	14.40	13.33
50	5.70	5.40	5.80	5.63	23.20	35.05	41.30	33.18	50	6.20	5.75	6.25	6.07	23.15	30.40	31.60	28.38
100	4.90	6.00	4.65	5.18	49.00	60.85	72.15	60.67	100	5.45	6.35	6.05	5.95	43.05	48.30	56.60	49.32
Average	5.38	5.77	5.80	5.65	28.30	37.35	43.42	36.36	Average	6.15	6.88	6.90	6.64	25.88	30.95	34.20	30.34
PCMGX									*PCPX*								
20	5.85	5.55	5.55	5.65	8.95	12.20	14.00	11.72	20	5.05	6.05	5.45	5.52	8.60	11.80	14.30	11.57
50	5.50	5.20	5.05	5.25	11.60	19.85	29.85	20.43	50	5.50	5.20	4.60	5.10	12.30	20.10	30.20	20.87
100	5.05	5.20	4.45	4.90	22.50	39.25	53.00	38.25	100	5.05	5.35	4.85	5.08	26.60	37.50	52.65	38.92
Average	5.47	5.32	5.02	5.27	14.35	23.77	32.28	23.47	Average	5.20	5.53	4.97	5.23	15.83	23.13	32.38	23.78
PCMGX2S									*PCPX2S*								
20	5.75	6.35	7.00	6.37	10.45	17.15	17.15	14.92	20	5.95	6.50	6.85	6.43	11.15	16.05	16.20	14.47
50	5.40	5.25	5.90	5.52	19.20	33.85	40.45	31.17	50	5.40	5.15	6.20	5.58	21.65	34.40	38.75	31.60
100	5.00	5.95	4.65	5.20	39.70	59.30	70.50	56.50	100	4.70	6.05	5.00	5.25	42.60	54.60	67.25	54.82
Average	5.38	5.85	5.85	5.69	23.12	36.77	42.70	34.19	Average	5.35	5.90	6.02	5.76	25.13	35.02	40.73	33.63

Table A49: High Heterogeneity – DGP2, Case a: Low Spatial Dependence - SMA Errors

	Heterogeneous									*Homogeneous*							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	-0.02	-0.17	-0.44	0.21	14.01	12.82	12.34	13.06	20	0.15	-0.22	-0.38	0.25	15.00	13.57	12.63	13.73
50	-0.23	0.26	-0.28	0.26	8.83	8.00	7.71	8.18	50	-0.25	0.27	-0.29	0.27	9.53	8.35	8.05	8.64
100	-0.24	-0.12	0.13	0.17	6.33	5.66	5.68	5.89	100	-0.22	-0.19	0.10	0.17	6.74	5.99	5.81	6.18
Average	0.17	0.18	0.28	0.21	9.73	8.82	8.58	9.04	Average	0.21	0.23	0.25	0.23	10.42	9.31	8.83	9.52
*SW**									*2WFE*								
20	0.08	-0.17	-0.43	0.23	13.89	12.81	12.34	13.01	20	0.53	0.16	-0.38	0.36	18.13	15.65	14.02	15.93
50	-0.24	0.26	-0.28	0.26	8.71	7.99	7.71	8.14	50	-0.27	0.33	-0.43	0.35	10.48	10.06	9.95	10.16
100	-0.23	-0.13	0.13	0.16	6.24	5.66	5.68	5.86	100	-0.21	-0.11	0.08	0.14	7.32	7.08	6.61	7.00
Average	0.18	0.18	0.28	0.22	9.61	8.82	8.58	9.00	Average	0.34	0.20	0.30	0.28	11.97	10.93	10.19	11.03
CCEMG									*CCEP*								
20	0.16	-0.15	-0.41	0.24	14.76	12.88	12.36	13.33	20	0.22	-0.18	-0.39	0.26	15.49	13.62	12.65	13.92
50	-0.21	0.23	-0.28	0.24	9.25	8.04	7.72	8.33	50	-0.21	0.30	-0.28	0.26	9.84	8.40	8.06	8.77
100	-0.16	-0.14	0.13	0.15	6.60	5.70	5.70	6.00	100	-0.20	-0.20	0.10	0.17	6.92	6.01	5.83	6.26
Average	0.18	0.17	0.28	0.21	10.20	8.87	8.59	9.22	Average	0.21	0.23	0.26	0.23	10.75	9.35	8.85	9.65
CCEMGX									*CCEPX*								
20	0.30	-0.12	-0.42	0.28	14.82	12.90	12.33	13.35	20	0.32	-0.21	-0.37	0.30	15.55	13.64	12.63	13.94
50	-0.22	0.25	-0.29	0.25	9.23	8.04	7.71	8.33	50	-0.19	0.29	-0.28	0.25	9.88	8.39	8.06	8.78
100	-0.20	-0.13	0.13	0.15	6.69	5.70	5.70	6.03	100	-0.18	-0.19	0.10	0.16	6.97	6.02	5.83	6.28
Average	0.24	0.17	0.28	0.23	10.25	8.88	8.58	9.24	Average	0.23	0.23	0.25	0.24	10.80	9.35	8.84	9.66
IPCMG									*IPCP*								
20	0.05	-0.14	-0.45	0.21	16.14	13.13	12.46	13.91	20	-0.07	-0.36	-0.58	0.34	16.55	14.79	13.94	15.09
50	-0.32	0.27	-0.27	0.29	9.62	8.08	7.74	8.48	50	-0.11	0.30	-0.26	0.22	10.14	8.77	8.43	9.11
100	-0.24	-0.10	0.14	0.16	6.66	5.71	5.69	6.02	100	-0.25	-0.22	0.10	0.19	7.07	6.07	5.92	6.35
Average	0.20	0.17	0.29	0.22	10.81	8.97	8.63	9.47	Average	0.14	0.29	0.31	0.25	11.25	9.88	9.43	10.19
PCMGX									*PCPX*								
20	0.00	-0.21	-0.44	0.22	15.24	12.93	12.39	13.52	20	0.02	-0.34	-0.35	0.23	15.89	13.73	12.78	14.13
50	-0.22	0.26	-0.27	0.25	9.42	8.09	7.73	8.41	50	-0.13	0.27	-0.30	0.23	10.02	8.52	8.10	8.88
100	-0.30	-0.17	0.13	0.20	6.89	5.77	5.69	6.12	100	-0.34	-0.20	0.12	0.22	7.21	6.08	5.85	6.38
Average	0.18	0.21	0.28	0.22	10.52	8.93	8.60	9.35	Average	0.16	0.27	0.26	0.23	11.04	9.44	8.91	9.80
PCMGX2S									*PCPX2S*								
20	0.06	-0.22	-0.46	0.24	15.80	12.94	12.42	13.72	20	0.03	-0.31	-0.52	0.29	16.73	14.38	13.41	14.84
50	-0.25	0.26	-0.27	0.26	9.90	8.14	7.74	8.59	50	-0.04	0.30	-0.28	0.21	10.40	8.82	8.39	9.21
100	-0.29	-0.15	0.13	0.19	7.15	5.80	5.69	6.21	100	-0.30	-0.21	0.11	0.21	7.50	6.16	5.95	6.54
Average	0.20	0.21	0.29	0.23	10.95	8.96	8.61	9.51	Average	0.12	0.27	0.30	0.23	11.55	9.79	9.25	10.19
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	5.70	6.80	6.95	6.48	10.55	12.40	10.90	11.28	20	6.50	6.85	6.05	6.47	10.00	10.95	11.05	10.67
50	4.95	5.45	4.95	5.12	21.30	23.55	24.85	23.23	50	5.70	5.55	5.50	5.58	18.20	21.95	22.95	21.03
100	4.95	4.65	5.90	5.17	34.05	41.85	42.15	39.35	100	5.35	5.30	5.45	5.37	30.15	35.90	41.55	35.87
Average	5.20	5.63	5.93	5.59	21.97	25.93	25.97	24.62	Average	5.85	5.90	5.67	5.81	19.45	22.93	25.18	22.52
*SW**									*2WFE*								
20	6.80	6.80	6.95	6.85	10.70	12.00	10.55	11.08	20	48.75	62.20	70.20	60.38	9.35	10.30	10.95	10.20
50	5.55	5.30	5.10	5.32	21.45	23.55	24.35	23.12	50	47.55	62.50	75.70	61.92	15.00	16.80	16.10	15.97
100	5.55	4.85	5.85	5.42	34.40	41.50	42.55	39.48	100	44.40	62.90	71.60	59.63	26.40	27.00	32.90	28.77
Average	5.97	5.65	5.97	5.86	22.18	25.68	25.82	24.56	Average	46.90	62.53	72.50	60.64	16.92	18.03	19.98	18.31
CCEMG									*CCEP*								
20	7.00	7.35	7.60	7.32	10.05	11.90	10.95	10.97	20	7.30	8.85	7.40	7.85	8.65	11.20	11.45	10.43
50	6.15	6.00	5.10	5.75	18.45	22.75	24.75	21.98	50	6.90	6.35	5.95	6.40	16.75	21.00	22.85	20.20
100	4.85	4.85	6.05	5.25	33.30	42.75	42.05	39.37	100	5.05	5.70	5.45	5.40	29.90	36.15	41.70	35.92
Average	6.00	6.07	6.25	6.11	20.60	25.80	25.92	24.11	Average	6.42	6.97	6.27	6.55	18.43	22.78	25.33	22.18
CCEMGX									*CCEPX*								
20	6.45	6.40	6.60	6.48	9.25	11.60	11.20	10.68	20	6.20	7.10	5.80	6.37	9.25	11.20	11.85	10.77
50	5.15	5.45	4.85	5.15	19.50	22.75	24.55	22.27	50	6.40	5.25	5.60	5.75	16.80	21.95	23.30	20.68
100	5.50	4.70	5.75	5.32	30.75	42.25	41.40	38.13	100	5.20	5.10	5.05	5.12	28.85	37.00	41.65	35.83
Average	5.70	5.52	5.73	5.65	19.83	25.53	25.72	23.69	Average	5.93	5.82	5.48	5.74	18.30	23.38	25.60	22.43
IPCMG									*IPCP*								
20	5.30	6.55	6.90	6.25	10.50	11.95	10.80	11.08	20	9.50	13.10	12.00	11.53	8.50	10.75	11.30	10.18
50	5.15	5.40	4.90	5.15	18.20	23.65	24.25	22.03	50	8.20	8.45	8.85	8.50	17.95	21.65	22.65	20.75
100	5.30	4.65	5.70	5.22	30.90	42.30	42.70	38.63	100	7.00	6.35	6.90	6.75	26.55	34.60	41.55	34.23
Average	5.25	5.53	5.83	5.54	19.87	25.97	25.92	23.92	Average	8.23	9.30	9.25	8.93	17.67	22.33	25.17	21.72
PCMGX									*PCPX*								
20	6.30	6.90	6.50	6.57	9.25	11.50	10.70	10.48	20	7.15	6.70	6.15	6.67	8.65	10.60	12.05	10.43
50	5.20	5.30	5.05	5.18	18.40	23.45	24.35	22.07	50	5.75	5.25	5.60	5.53	17.45	22.40	22.75	20.87
100	4.80	5.05	5.65	5.17	30.65	39.90	42.75	37.77	100	5.30	5.05	5.05	5.13	27.05	35.00	41.85	34.63
Average	5.43	5.75	5.73	5.64	19.43	24.95	25.93	23.44	Average	6.07	5.67	5.60	5.78	17.72	22.67	25.55	21.98
PCMGX2S									*PCPX2S*								
20	6.35	6.55	7.00	6.63	8.85	12.35	11.25	10.82	20	9.70	9.85	10.35	9.97	8.35	9.90	11.45	9.90
50	5.50	5.35	4.80	5.22	17.20	23.80	24.40	21.80	50	8.00	8.10	7.65	7.92	16.95	22.85	22.40	20.73
100	4.90	4.95	5.60	5.15	28.80	40.15	43.50	37.48	100	6.65	5.95	6.25	6.28	26.95	34.80	41.10	34.28
Average	5.58	5.62	5.80	5.67	18.28	25.43	26.38	23.37	Average	8.12	7.97	8.08	8.06	17.42	22.52	24.98	21.64

Table A50: High Heterogeneity – DGP2, Case *b*: High Spatial Dependence - SMA Errors

	Heterogeneous									*Homogeneous*							
T	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	-0.05	-0.17	-0.48	0.23	14.39	12.90	12.40	13.23	20	0.17	-0.23	-0.41	0.27	15.24	13.64	12.67	13.85
50	-0.27	0.25	-0.29	0.27	9.01	8.06	7.74	8.27	50	-0.26	0.27	-0.29	0.27	9.67	8.41	8.08	8.72
100	-0.24	-0.13	0.15	0.18	6.46	5.69	5.69	5.95	100	-0.22	-0.19	0.11	0.17	6.84	6.02	5.82	6.22
Average	0.19	0.18	0.30	0.23	9.95	8.89	8.61	9.15	Average	0.22	0.23	0.27	0.24	10.58	9.36	8.86	9.60
*SW**									*2WFE*								
20	0.06	-0.16	-0.47	0.23	14.23	12.89	12.40	13.17	20	0.55	0.17	-0.40	0.37	18.30	15.65	14.02	15.99
50	-0.27	0.25	-0.29	0.27	8.89	8.06	7.74	8.23	50	-0.27	0.34	-0.44	0.35	10.55	10.08	9.96	10.20
100	-0.22	-0.14	0.15	0.17	6.36	5.69	5.69	5.92	100	-0.20	-0.12	0.09	0.14	7.35	7.08	6.62	7.02
Average	0.18	0.18	0.30	0.22	9.83	8.88	8.61	9.11	Average	0.34	0.21	0.31	0.29	12.07	10.94	10.20	11.07
CCEMG									*CCEP*								
20	0.16	-0.14	-0.43	0.24	15.08	12.93	12.39	13.47	20	0.28	-0.20	-0.40	0.29	15.75	13.67	12.67	14.03
50	-0.26	0.23	-0.30	0.26	9.47	8.11	7.75	8.44	50	-0.24	0.30	-0.30	0.28	9.98	8.47	8.10	8.85
100	-0.17	-0.15	0.14	0.16	6.76	5.72	5.71	6.06	100	-0.20	-0.21	0.11	0.17	7.04	6.04	5.84	6.31
Average	0.20	0.17	0.29	0.22	10.44	8.92	8.62	9.33	Average	0.24	0.24	0.27	0.25	10.93	9.39	8.87	9.73
CCEMGX									*CCEPX*								
20	0.26	-0.10	-0.44	0.27	15.22	12.96	12.37	13.52	20	0.36	-0.20	-0.39	0.32	15.77	13.68	12.65	14.04
50	-0.29	0.25	-0.30	0.28	9.43	8.12	7.74	8.43	50	-0.22	0.30	-0.29	0.27	10.01	8.46	8.09	8.85
100	-0.21	-0.15	0.14	0.16	6.85	5.73	5.72	6.10	100	-0.17	-0.20	0.11	0.16	7.08	6.05	5.85	6.33
Average	0.25	0.17	0.29	0.24	10.50	8.94	8.61	9.35	Average	0.25	0.23	0.27	0.25	10.95	9.40	8.86	9.74
IPCMG									*IPCP*								
20	-0.07	-0.18	-0.45	0.23	15.12	12.86	12.39	13.45	20	-0.11	-0.40	-0.48	0.33	16.37	14.25	13.20	14.60
50	-0.16	0.24	-0.30	0.23	9.42	8.10	7.76	8.43	50	-0.08	0.29	-0.29	0.22	10.01	8.69	8.26	8.99
100	-0.23	-0.13	0.14	0.17	6.68	5.74	5.70	6.04	100	-0.22	-0.21	0.11	0.18	7.11	6.08	5.90	6.36
Average	0.15	0.18	0.30	0.21	10.41	8.90	8.62	9.31	Average	0.14	0.30	0.30	0.25	11.16	9.67	9.12	9.98
PCMGX									*PCPX*								
20	-0.09	-0.21	-0.47	0.26	15.83	13.06	12.46	13.79	20	0.01	-0.34	-0.37	0.24	16.29	13.81	12.84	14.31
50	-0.26	0.26	-0.28	0.27	9.68	8.18	7.76	8.54	50	-0.15	0.27	-0.31	0.25	10.18	8.61	8.13	8.97
100	-0.31	-0.19	0.14	0.21	7.08	5.82	5.70	6.20	100	-0.34	-0.21	0.14	0.23	7.34	6.13	5.87	6.45
Average	0.22	0.22	0.30	0.25	10.86	9.02	8.64	9.51	Average	0.17	0.27	0.27	0.24	11.27	9.51	8.95	9.91
PCMGX2S									*PCPX2S*								
20	-0.02	-0.25	-0.45	0.24	16.10	12.94	12.41	13.82	20	-0.06	-0.35	-0.43	0.28	16.73	14.15	13.04	14.64
50	-0.17	0.24	-0.29	0.24	10.04	8.21	7.77	8.67	50	-0.03	0.27	-0.33	0.21	10.38	8.77	8.29	9.14
100	-0.28	-0.18	0.14	0.20	7.27	5.85	5.71	6.28	100	-0.29	-0.20	0.12	0.20	7.54	6.20	5.92	6.55
Average	0.16	0.22	0.29	0.22	11.14	9.00	8.63	9.59	Average	0.12	0.27	0.29	0.23	11.55	9.70	9.08	10.11
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	5.65	6.90	7.05	6.53	10.70	11.95	10.35	11.00	20	6.05	6.95	6.20	6.40	10.25	11.50	10.85	10.87
50	5.00	5.55	4.85	5.13	19.75	23.60	24.95	22.77	50	5.70	5.50	5.50	5.57	17.20	21.20	22.80	20.40
100	4.50	4.80	5.60	4.97	34.70	41.85	43.15	39.90	100	5.05	4.95	5.40	5.13	29.70	37.30	41.40	36.13
Average	5.05	5.75	5.83	5.54	21.72	25.80	26.15	24.56	Average	5.60	5.80	5.70	5.70	19.05	23.33	25.02	22.47
*SW**									*2WFE*								
20	6.55	7.20	7.00	6.92	10.95	12.10	10.25	11.10	20	47.50	61.65	69.15	59.43	9.30	10.55	11.00	10.28
50	5.95	5.15	4.85	5.32	19.75	23.85	25.05	22.88	50	46.15	60.80	75.45	60.80	15.50	17.05	16.00	16.18
100	5.30	4.95	5.55	5.27	34.50	42.05	43.15	39.90	100	43.00	61.85	71.05	58.63	26.85	27.00	32.30	28.72
Average	5.93	5.77	5.80	5.83	21.73	26.00	26.15	24.63	Average	45.55	61.43	71.88	59.62	17.22	18.20	19.77	18.39
CCEMG									*CCEP*								
20	7.25	8.15	7.70	7.70	10.10	11.90	10.60	10.87	20	7.35	9.00	7.45	7.93	9.10	11.40	11.15	10.55
50	6.05	6.00	5.55	5.87	19.15	21.75	23.90	21.60	50	6.50	6.35	6.10	6.32	16.95	20.25	22.85	20.02
100	5.35	4.80	5.55	5.23	31.00	41.80	43.00	38.60	100	5.10	5.55	5.40	5.35	29.65	35.55	41.75	35.65
Average	6.22	6.32	6.27	6.27	20.08	25.15	25.83	23.69	Average	6.32	6.97	6.32	6.53	18.57	22.40	25.25	22.07
CCEMGX									*CCEPX*								
20	6.15	6.70	6.35	6.40	8.85	12.30	11.25	10.80	20	6.15	6.85	5.95	6.32	9.50	11.00	11.45	10.65
50	5.35	5.65	4.80	5.27	18.15	22.55	24.75	21.82	50	6.20	5.40	5.50	5.70	15.15	22.05	22.65	19.95
100	5.45	4.70	5.35	5.17	29.25	41.20	42.55	37.67	100	5.40	5.20	5.10	5.23	28.20	35.45	42.10	35.25
Average	5.65	5.68	5.50	5.61	18.75	25.35	26.18	23.43	Average	5.92	5.82	5.52	5.75	17.62	22.83	25.40	21.95
IPCMG									*IPCP*								
20	5.10	6.45	6.55	6.03	11.75	11.85	11.00	11.53	20	10.00	10.35	8.50	9.62	8.85	9.60	10.95	9.80
50	4.80	5.15	4.95	4.97	19.85	24.30	24.70	22.95	50	8.35	7.65	7.10	7.70	17.25	21.75	23.05	20.68
100	4.75	4.85	5.70	5.10	32.05	41.75	42.25	38.68	100	6.65	6.05	6.15	6.28	28.65	35.90	41.50	35.35
Average	4.88	5.48	5.73	5.37	21.22	25.97	25.98	24.39	Average	8.33	8.02	7.25	7.87	18.25	22.42	25.17	21.94
PCMGX									*PCPX*								
20	6.10	7.10	6.55	6.58	8.80	11.10	10.80	10.23	20	6.60	6.70	5.80	6.37	9.50	10.60	12.10	10.73
50	4.85	5.40	4.90	5.05	18.35	24.20	25.00	22.52	50	5.85	5.55	5.50	5.63	16.95	21.05	22.40	20.13
100	5.10	5.15	5.45	5.23	28.65	38.90	43.10	36.88	100	5.30	4.85	4.95	5.03	27.15	36.00	42.60	35.25
Average	5.35	5.88	5.63	5.62	18.60	24.73	26.30	23.21	Average	5.92	5.70	5.42	5.68	17.87	22.55	25.70	22.04
PCMGX2S									*PCPX2S*								
20	5.90	6.70	6.50	6.37	9.60	11.60	11.10	10.77	20	9.15	8.95	7.85	8.65	8.15	10.55	11.50	10.07
50	5.90	5.40	5.10	5.47	16.35	23.35	24.15	21.28	50	7.00	6.90	6.90	6.93	16.75	21.55	23.75	20.68
100	5.15	5.15	5.50	5.27	26.30	39.45	42.65	36.13	100	6.60	5.75	5.65	6.00	25.20	35.20	42.30	34.23
Average	5.65	5.75	5.70	5.70	17.42	24.80	25.97	22.73	Average	7.58	7.20	6.80	7.19	16.70	22.43	25.85	21.66

Table A51: High Heterogeneity – DGP4, Case e: Low Spatial Dependence & Low Factor Dependence – SMA Errors

	Heterogeneous									*Homogeneous*								
	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)				
N \ T	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average	
*MG**									*FE**									
20	17.66	18.17	17.02	17.61	24.76	24.15	22.20	23.70	20	21.16	22.61	21.65	21.81	29.06	29.09	27.56	28.57	
50	18.75	17.64	17.36	17.92	22.84	20.27	19.75	20.95	50	22.38	22.48	22.10	22.32	26.97	25.54	24.83	25.78	
100	17.88	17.76	17.69	17.78	20.46	19.38	19.05	19.63	100	22.08	22.34	22.66	22.36	25.33	24.23	24.26	24.61	
Average	18.09	17.85	17.36	17.77	22.68	21.27	20.34	21.43	Average	21.87	22.48	22.13	22.16	27.12	26.29	25.55	26.32	
*SW**									*2WFE*									
20	18.53	18.54	17.20	18.09	25.18	24.36	22.34	23.96	20	-0.37	0.22	-0.26	0.28	16.70	16.14	15.11	15.98	
50	19.58	18.08	17.55	18.40	23.37	20.65	19.92	21.31	50	-0.02	-0.31	-0.28	0.20	10.95	9.74	9.64	10.11	
100	18.85	18.15	17.91	18.30	21.35	19.73	19.26	20.11	100	-0.06	-0.29	0.14	0.16	7.41	6.97	7.01	7.13	
Average	18.99	18.26	17.55	18.27	23.30	21.58	20.51	21.79	Average	0.15	0.27	0.23	0.22	11.69	10.95	10.59	11.07	
CCEMG									*CCEP*									
20	-0.46	0.14	-0.31	0.30	14.12	12.91	12.41	13.15	20	-0.67	0.27	-0.29	0.41	15.51	13.95	13.06	14.17	
50	0.38	-0.40	0.05	0.28	9.61	8.00	7.90	8.50	50	0.07	-0.27	-0.01	0.11	10.02	8.44	8.18	8.88	
100	-0.11	-0.24	0.13	0.16	6.49	5.79	5.55	5.94	100	-0.10	-0.33	0.14	0.19	6.95	6.10	5.80	6.28	
Average	0.32	0.26	0.16	0.25	10.07	8.90	8.62	9.20	Average	0.28	0.29	0.15	0.24	10.83	9.50	9.01	9.78	
CCEMGX									*CCEPX*									
20	-0.41	0.15	-0.31	0.29	14.22	12.94	12.41	13.19	20	-0.70	0.26	-0.28	0.41	15.53	13.95	13.06	14.18	
50	0.36	-0.41	0.06	0.27	9.69	8.01	7.91	8.54	50	0.04	-0.28	0.00	0.11	10.05	8.44	8.18	8.89	
100	-0.13	-0.25	0.13	0.17	6.50	5.80	5.55	5.95	100	-0.10	-0.33	0.14	0.19	6.95	6.09	5.80	6.28	
Average	0.30	0.27	0.16	0.24	10.14	8.92	8.63	9.23	Average	0.28	0.29	0.14	0.24	10.85	9.49	9.01	9.78	
IPCMG									*IPCP*									
20	-0.79	0.19	-0.31	0.43	14.86	13.00	12.41	13.42	20	-1.81	-1.38	-1.25	1.48	16.73	15.49	14.58	15.60	
50	0.45	-0.35	0.06	0.29	9.54	7.96	7.87	8.46	50	-1.05	-1.63	-1.41	1.36	10.60	9.29	9.21	9.70	
100	0.01	-0.22	0.13	0.12	6.29	5.71	5.52	5.84	100	-1.28	-1.55	-1.16	1.33	7.49	6.96	6.60	7.02	
Average	0.42	0.25	0.17	0.28	10.23	8.89	8.60	9.24	Average	1.38	1.52	1.28	1.39	11.61	10.58	10.13	10.77	
PCMGX									*PCPX*									
20	0.58	0.60	-0.24	0.47	16.80	14.14	12.67	14.54	20	0.36	0.51	-0.30	0.39	16.80	14.63	12.97	14.80	
50	0.70	-0.17	0.14	0.34	11.48	8.60	8.10	9.40	50	0.39	-0.10	0.07	0.19	11.22	8.84	8.30	9.45	
100	0.38	-0.02	0.15	0.18	7.71	6.21	5.73	6.55	100	0.38	-0.11	0.17	0.22	7.75	6.36	5.92	6.68	
Average	0.55	0.26	0.18	0.33	11.99	9.65	8.83	10.16	Average	0.38	0.24	0.18	0.27	11.92	9.94	9.06	10.31	
PCMGX2S									*PCPX2S*									
20	-0.23	0.33	-0.30	0.29	15.08	13.12	12.36	13.52	20	-0.47	0.17	-0.38	0.34	15.94	14.11	12.94	14.33	
50	0.38	-0.34	0.09	0.27	10.20	8.05	7.90	8.72	50	0.03	-0.29	-0.02	0.11	10.40	8.49	8.20	9.03	
100	-0.06	-0.23	0.15	0.14	6.73	5.79	5.54	6.02	100	-0.07	-0.31	0.15	0.18	7.12	6.11	5.76	6.33	
Average	0.22	0.30	0.18	0.23	10.67	8.99	8.60	9.42	Average	0.19	0.26	0.18	0.21	11.15	9.57	8.97	9.90	
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)				
*MG**									*FE**									
20	20.65	25.30	22.85	22.93	14.60	13.50	16.45	14.85	20	24.30	28.55	28.70	27.18	11.15	13.15	13.55	12.62	
50	40.65	45.30	49.10	45.02	18.40	21.25	26.50	22.05	50	47.45	54.85	55.60	52.63	15.50	20.05	19.40	18.32	
100	62.10	71.95	74.95	69.67	26.10	37.20	38.65	33.98	100	68.05	78.65	81.05	75.92	22.50	30.00	29.65	27.38	
Average	41.13	47.52	48.97	45.87	19.70	23.98	27.20	23.63	Average	46.60	54.02	55.12	51.91	16.38	21.07	20.87	19.44	
*SW**									*2WFE*									
20	22.95	25.50	23.75	24.07	13.80	14.15	15.70	14.55	20	48.30	65.70	74.35	62.78	9.00	9.75	9.20	9.32	
50	45.05	47.70	49.95	47.57	18.60	22.40	26.40	22.47	50	47.35	63.90	73.05	61.43	14.10	17.40	17.20	16.23	
100	67.05	74.30	75.65	72.33	25.05	36.50	39.15	33.57	100	47.45	65.65	76.15	63.08	27.55	28.90	31.55	29.33	
Average	45.02	49.17	49.78	47.99	19.15	24.35	27.08	23.53	Average	47.70	65.08	74.52	62.43	16.88	18.68	19.32	18.29	
CCEMG									*CCEP*									
20	6.50	7.75	8.25	7.50	11.00	11.00	10.50	10.83	20	7.75	7.60	8.20	7.85	10.00	10.80	10.35	10.38	
50	6.15	5.95	6.65	6.25	16.20	21.60	22.40	20.07	50	6.05	5.80	6.50	6.12	17.15	20.75	21.55	19.82	
100	5.10	6.30	4.85	5.42	32.95	37.00	44.15	38.03	100	5.20	5.80	5.60	5.53	29.30	34.60	40.45	34.78	
Average	5.92	6.67	6.58	6.39	20.05	23.20	25.68	22.98	Average	6.33	6.40	6.77	6.50	18.82	22.05	24.12	21.66	
CCEMGX									*CCEPX*									
20	5.15	6.50	7.10	6.25	10.70	10.55	10.55	10.60	20	6.00	6.75	6.80	6.52	9.50	10.40	10.15	10.02	
50	5.90	5.20	6.10	5.73	17.30	21.30	22.35	20.32	50	5.55	5.20	6.00	5.58	17.80	20.05	21.55	19.80	
100	5.00	6.05	4.65	5.23	32.50	35.75	44.40	37.55	100	4.90	5.25	5.25	5.13	29.30	34.55	40.60	34.82	
Average	5.35	5.92	5.95	5.74	20.17	22.53	25.77	22.82	Average	5.48	5.73	6.02	5.74	18.87	21.67	24.10	21.54	
IPCMG									*IPCP*									
20	5.85	6.35	6.90	6.37	9.20	10.65	10.75	10.20	20	9.40	11.55	11.35	10.77	8.30	8.90	9.35	8.85	
50	5.75	5.30	5.65	5.57	16.50	21.90	22.45	20.28	50	7.50	7.95	8.65	8.03	14.85	15.75	13.80	14.80	
100	4.90	5.80	4.80	5.17	35.70	39.15	44.25	39.70	100	7.00	8.75	8.30	8.02	21.15	20.35	23.65	21.72	
Average	5.50	5.82	5.78	5.70	20.47	23.90	25.82	23.39	Average	7.97	9.42	9.43	8.94	14.77	15.00	15.60	15.12	
PCMGX									*PCPX*									
20	5.90	6.45	6.35	6.23	9.55	11.05	9.85	10.15	20	5.95	6.25	6.50	6.23	9.30	11.65	10.55	10.50	
50	5.30	5.30	5.25	5.28	14.80	19.55	23.80	19.38	50	5.50	4.20	5.25	4.98	14.45	19.55	22.35	18.78	
100	5.50	5.35	5.00	5.28	26.85	35.20	40.60	34.22	100	4.90	5.50	5.55	5.32	26.75	32.05	37.05	31.95	
Average	5.57	5.70	5.53	5.60	17.07	21.93	24.75	21.25	Average	5.45	5.32	5.77	5.51	16.83	21.08	23.32	20.41	
PCMGX2S									*PCPX2S*									
20	5.65	6.60	6.70	6.32	9.65	11.55	10.90	10.70	20	7.30	7.75	7.95	7.67	9.15	10.90	9.80	9.95	
50	5.85	5.00	6.10	5.65	16.00	22.25	23.70	20.65	50	5.95	5.35	6.55	5.95	16.25	21.55	20.85	19.55	
100	5.10	5.85	4.40	5.12	31.15	36.60	44.75	37.50	100	5.40	5.50	5.50	5.47	27.30	34.65	39.65	33.87	
Average	5.53	5.82	5.73	5.69	18.93	23.47	26.45	22.95	Average	6.22	6.20	6.67	6.36	17.57	22.37	23.43	21.12	

Table A52: High Heterogeneity – DGP4, Case f: Low Spatial Dependence & High Factor Dependence – SMA Errors

	Heterogeneous									*Homogeneous*							
	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	35.74	36.24	34.43	35.47	44.21	42.67	39.32	42.07	20	43.19	45.13	43.67	44.00	51.59	51.37	48.73	50.56
50	37.25	35.67	34.72	35.88	42.61	38.59	37.05	39.41	50	44.76	45.18	44.30	44.74	50.68	48.48	46.88	48.68
100	35.87	35.75	35.28	35.63	39.60	37.68	36.70	38.00	100	44.24	45.02	45.17	44.81	49.06	47.33	46.85	47.75
Average	36.29	35.89	34.81	35.66	42.14	39.65	37.69	39.83	Average	44.06	45.11	44.38	44.52	50.44	49.06	47.49	49.00
*SW**									*2WFE*								
20	38.53	37.50	35.14	37.05	46.24	43.58	39.91	43.24	20	-0.33	0.23	-0.25	0.27	17.12	16.49	15.50	16.37
50	39.70	37.08	35.42	37.40	44.63	39.89	37.71	40.74	50	-0.03	-0.32	-0.29	0.22	11.30	10.01	9.88	10.40
100	38.65	37.07	36.03	37.25	42.32	38.95	37.45	39.57	100	-0.07	-0.28	0.14	0.16	7.61	7.13	7.16	7.30
Average	38.96	37.21	35.53	37.24	44.39	40.81	38.35	41.19	Average	0.15	0.28	0.23	0.22	12.01	11.21	10.85	11.36
CCEMG									*CCEP*								
20	-0.49	0.13	-0.29	0.30	14.31	13.06	12.52	13.30	20	-0.69	0.28	-0.26	0.41	15.70	14.12	13.19	14.34
50	0.37	-0.40	0.05	0.27	9.65	8.04	7.93	8.54	50	0.07	-0.27	0.00	0.12	10.05	8.47	8.21	8.91
100	-0.11	-0.25	0.14	0.16	6.51	5.80	5.56	5.96	100	-0.10	-0.33	0.14	0.19	6.96	6.11	5.81	6.29
Average	0.32	0.26	0.16	0.25	10.16	8.97	8.67	9.26	Average	0.29	0.29	0.14	0.24	10.91	9.57	9.07	9.85
CCEMGX									*CCEPX*								
20	-0.40	0.19	-0.29	0.29	14.53	13.13	12.53	13.40	20	-0.69	0.25	-0.26	0.40	15.72	14.12	13.19	14.34
50	0.37	-0.41	0.06	0.28	9.76	8.06	7.95	8.59	50	0.05	-0.28	0.01	0.11	10.08	8.47	8.21	8.92
100	-0.12	-0.25	0.13	0.17	6.53	5.81	5.56	5.97	100	-0.11	-0.33	0.14	0.19	6.96	6.11	5.80	6.29
Average	0.30	0.28	0.16	0.25	10.27	9.00	8.68	9.32	Average	0.28	0.29	0.13	0.23	10.92	9.57	9.07	9.85
IPCMG									*IPCP*								
20	-0.89	0.19	-0.31	0.46	15.00	12.96	12.34	13.43	20	-1.01	-0.44	-0.51	0.65	16.39	15.50	14.56	15.49
50	0.27	-0.38	0.06	0.24	9.50	7.94	7.87	8.44	50	-0.17	-0.66	-0.32	0.38	10.64	9.22	9.25	9.70
100	-0.09	-0.23	0.13	0.15	6.27	5.71	5.52	5.84	100	-0.43	-0.52	0.05	0.33	7.32	6.94	6.71	6.99
Average	0.42	0.27	0.17	0.28	10.26	8.87	8.58	9.23	Average	0.54	0.54	0.29	0.46	11.45	10.55	10.17	10.73
PCMGX									*PCPX*								
20	1.59	1.12	-0.10	0.94	22.44	16.81	13.68	17.64	20	1.22	0.90	-0.25	0.79	20.82	16.61	13.85	17.09
50	1.21	0.02	0.22	0.49	15.33	10.14	8.69	11.39	50	0.83	0.09	0.12	0.35	13.70	10.02	8.82	10.84
100	0.85	0.21	0.17	0.41	10.32	7.23	6.20	7.92	100	0.80	0.05	0.18	0.35	9.69	7.15	6.31	7.72
Average	1.22	0.45	0.16	0.61	16.03	11.39	9.53	12.32	Average	0.95	0.35	0.18	0.49	14.74	11.26	9.66	11.89
PCMGX2S									*PCPX2S*								
20	-0.31	0.39	-0.26	0.32	15.66	13.33	12.40	13.79	20	-0.49	0.27	-0.35	0.37	15.94	14.13	12.86	14.31
50	0.23	-0.33	0.11	0.22	10.34	8.08	7.90	8.78	50	0.03	-0.30	-0.02	0.12	10.45	8.49	8.17	9.04
100	-0.06	-0.23	0.15	0.14	6.79	5.80	5.54	6.04	100	-0.04	-0.32	0.16	0.17	7.09	6.12	5.76	6.32
Average	0.20	0.31	0.17	0.23	10.93	9.07	8.61	9.54	Average	0.19	0.29	0.18	0.22	11.16	9.58	8.93	9.89
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	35.65	44.90	47.05	42.53	9.50	10.65	11.70	10.62	20	45.05	55.70	57.15	52.63	9.95	9.80	10.55	10.10
50	61.55	78.30	82.30	74.05	11.10	15.00	17.45	14.52	50	75.80	85.95	90.25	84.00	11.15	13.75	13.40	12.77
100	84.10	95.95	98.05	92.70	17.50	25.40	25.60	22.83	100	90.10	98.50	99.10	95.90	13.65	19.55	18.95	17.38
Average	60.43	73.05	75.80	69.76	12.70	17.02	18.25	15.99	Average	70.32	80.05	82.17	77.51	11.58	14.37	14.30	13.42
*SW**									*2WFE*								
20	41.15	47.50	49.00	45.88	9.25	10.80	11.85	10.63	20	47.30	64.05	74.15	61.83	8.50	9.10	9.20	8.93
50	71.05	81.10	83.80	78.65	12.40	14.95	17.45	14.93	50	45.60	63.60	72.80	60.67	13.90	17.00	16.00	15.63
100	89.45	97.25	98.35	95.02	16.25	25.30	25.20	22.25	100	45.70	64.10	75.50	61.77	26.30	26.70	31.45	28.15
Average	67.22	75.28	77.05	73.18	12.63	17.02	18.17	15.94	Average	46.20	63.92	74.15	61.42	16.23	17.60	18.88	17.57
CCEMG									*CCEP*								
20	6.35	7.90	8.05	7.43	10.30	10.60	10.30	10.40	20	7.50	8.05	8.20	7.92	8.95	10.95	10.05	9.98
50	6.10	5.80	6.60	6.17	16.55	21.65	22.20	20.13	50	5.90	5.85	6.45	6.07	17.80	20.70	21.30	19.93
100	5.05	6.45	4.95	5.48	32.60	36.55	44.00	37.72	100	5.15	5.60	5.55	5.43	29.35	34.65	40.05	34.68
Average	5.83	6.72	6.53	6.36	19.82	22.93	25.50	22.75	Average	6.18	6.50	6.73	6.47	18.70	22.10	23.80	21.53
CCEMGX									*CCEPX*								
20	4.90	6.05	6.90	5.95	10.35	10.70	10.50	10.52	20	5.60	6.65	7.00	6.42	9.15	10.70	10.00	9.95
50	6.00	5.20	6.15	5.78	17.40	21.25	22.40	20.35	50	5.30	5.05	5.95	5.43	17.60	20.35	21.35	19.77
100	5.00	6.15	4.70	5.28	31.80	35.10	44.50	37.13	100	4.80	5.25	5.10	5.05	29.75	34.35	40.00	34.70
Average	5.30	5.80	5.92	5.67	19.85	22.35	25.80	22.67	Average	5.23	5.65	6.02	5.63	18.83	21.80	23.78	21.47
IPCMG									*IPCP*								
20	5.20	6.55	6.85	6.20	9.70	10.05	11.20	10.32	20	8.00	10.40	9.95	9.45	8.25	9.55	10.35	9.38
50	6.20	5.45	5.75	5.80	16.05	21.85	23.10	20.33	50	7.35	6.25	7.55	7.05	15.50	18.55	15.60	16.55
100	5.05	5.90	4.90	5.28	35.05	39.10	44.10	39.42	100	6.20	7.20	7.10	6.83	26.90	26.15	32.85	28.63
Average	5.48	5.97	5.83	5.76	20.27	23.67	26.13	23.36	Average	7.18	7.95	8.20	7.78	16.88	18.08	19.60	18.19
PCMGX									*PCPX*								
20	5.50	6.00	5.85	5.78	8.35	10.35	9.90	9.53	20	5.95	6.00	5.90	5.95	8.25	9.70	9.85	9.27
50	5.35	5.20	5.55	5.37	11.35	15.60	19.80	15.58	50	5.25	5.15	4.95	5.12	11.85	14.50	20.60	15.65
100	5.25	5.05	5.15	5.15	19.05	28.70	34.75	27.50	100	5.00	4.75	5.30	5.02	21.65	27.70	33.70	27.68
Average	5.37	5.42	5.52	5.43	12.92	18.22	21.48	17.54	Average	5.40	5.30	5.38	5.36	13.92	17.30	21.38	17.53
PCMGX2S									*PCPX2S*								
20	5.80	6.35	6.75	6.30	9.25	12.20	10.80	10.75	20	6.60	7.35	7.55	7.17	8.85	11.00	9.55	9.80
50	5.75	5.30	6.00	5.68	14.95	21.25	23.60	19.93	50	6.10	5.10	6.25	5.82	15.85	20.85	20.50	19.07
100	5.05	5.95	4.50	5.17	30.00	36.70	44.85	37.18	100	5.15	5.70	5.40	5.42	28.10	34.50	39.95	34.18
Average	5.53	5.87	5.75	5.72	18.07	23.38	26.42	22.62	Average	5.95	6.05	6.40	6.13	17.60	22.12	23.33	21.02

Table A53: High Heterogeneity – DGP4, Case *g*: High Spatial Dependence & Low Factor Dependence – SMA Errors

	Heterogeneous									*Homogeneous*							
	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	17.64	18.21	17.02	17.62	24.89	24.23	22.21	23.78	20	21.16	22.65	21.66	21.82	29.17	29.14	27.58	28.63
50	18.73	17.63	17.35	17.91	22.90	20.28	19.74	20.97	50	22.39	22.48	22.09	22.32	27.00	25.56	24.83	25.80
100	17.88	17.76	17.69	17.78	20.50	19.40	19.06	19.65	100	22.08	22.34	22.65	22.36	25.35	24.25	24.27	24.62
Average	18.08	17.87	17.35	17.77	22.76	21.30	20.34	21.47	Average	21.88	22.49	22.13	22.17	27.17	26.31	25.56	26.35
*SW**									*2WFE*								
20	18.56	18.61	17.22	18.13	25.34	24.45	22.37	24.05	20	-0.33	0.26	-0.25	0.28	16.77	16.13	15.14	16.01
50	19.63	18.10	17.55	18.43	23.46	20.68	19.92	21.35	50	-0.02	-0.31	-0.29	0.21	10.98	9.76	9.64	10.13
100	18.90	18.17	17.92	18.33	21.43	19.77	19.28	20.16	100	-0.07	-0.29	0.15	0.17	7.45	6.98	7.01	7.15
Average	19.03	18.29	17.56	18.30	23.41	21.63	20.52	21.85	Average	0.14	0.28	0.23	0.22	11.73	10.96	10.60	11.09
CCEMG									*CCEP*								
20	-0.44	0.21	-0.34	0.33	14.33	12.99	12.43	13.25	20	-0.67	0.35	-0.31	0.44	15.60	13.97	13.08	14.22
50	0.37	-0.39	0.02	0.26	9.85	8.05	7.89	8.60	50	0.07	-0.27	-0.03	0.12	10.13	8.50	8.18	8.94
100	-0.09	-0.24	0.14	0.15	6.63	5.84	5.56	6.01	100	-0.08	-0.32	0.14	0.18	7.02	6.14	5.81	6.33
Average	0.30	0.28	0.16	0.25	10.27	8.96	8.63	9.29	Average	0.27	0.31	0.16	0.25	10.92	9.54	9.02	9.83
CCEMGX									*CCEPX*								
20	-0.38	0.23	-0.32	0.31	14.46	13.03	12.43	13.31	20	-0.73	0.33	-0.30	0.45	15.63	13.96	13.07	14.22
50	0.33	-0.40	0.03	0.26	9.97	8.07	7.90	8.65	50	0.04	-0.28	-0.02	0.11	10.17	8.49	8.18	8.95
100	-0.12	-0.25	0.13	0.17	6.65	5.85	5.56	6.02	100	-0.08	-0.33	0.13	0.18	7.03	6.14	5.81	6.32
Average	0.28	0.29	0.16	0.24	10.36	8.98	8.63	9.33	Average	0.29	0.31	0.15	0.25	10.94	9.53	9.02	9.83
IPCMG									*IPCP*								
20	-0.45	0.27	-0.35	0.36	14.49	13.00	12.50	13.33	20	-1.80	-1.46	-1.34	1.53	16.98	15.49	14.58	15.68
50	0.52	-0.32	0.02	0.29	9.69	8.03	7.88	8.53	50	-1.14	-1.67	-1.50	1.44	10.68	9.38	9.26	9.77
100	0.05	-0.22	0.12	0.13	6.39	5.76	5.54	5.90	100	-1.31	-1.57	-1.19	1.36	7.55	6.99	6.61	7.05
Average	0.34	0.27	0.16	0.26	10.19	8.93	8.64	9.25	Average	1.42	1.56	1.34	1.44	11.74	10.62	10.15	10.83
PCMGX									*PCPX*								
20	0.58	0.65	-0.25	0.49	17.21	14.25	12.69	14.72	20	0.35	0.57	-0.31	0.41	17.01	14.68	12.99	14.89
50	0.65	-0.17	0.12	0.31	11.74	8.67	8.09	9.50	50	0.36	-0.11	0.05	0.17	11.38	8.89	8.29	9.52
100	0.38	-0.01	0.16	0.18	7.84	6.27	5.74	6.62	100	0.38	-0.11	0.17	0.22	7.81	6.41	5.93	6.72
Average	0.54	0.28	0.17	0.33	12.26	9.73	8.84	10.28	Average	0.36	0.26	0.17	0.27	12.06	10.00	9.07	10.38
PCMGX2S									*PCPX2S*								
20	-0.21	0.36	-0.32	0.29	15.21	13.19	12.38	13.59	20	-0.46	0.26	-0.37	0.36	16.04	14.11	12.95	14.36
50	0.40	-0.32	0.07	0.26	10.44	8.10	7.89	8.81	50	0.01	-0.30	-0.04	0.11	10.53	8.56	8.19	9.09
100	-0.02	-0.22	0.15	0.13	6.90	5.85	5.55	6.10	100	-0.06	-0.31	0.15	0.17	7.21	6.16	5.77	6.38
Average	0.21	0.30	0.18	0.23	10.85	9.05	8.61	9.50	Average	0.18	0.29	0.18	0.22	11.26	9.61	8.97	9.95
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	20.05	25.20	22.80	22.68	13.65	14.85	15.95	14.82	20	24.30	28.10	28.70	27.03	11.30	12.55	13.30	12.38
50	40.25	45.15	48.50	44.63	17.65	22.45	26.55	22.22	50	46.90	54.35	55.25	52.17	15.45	19.45	20.35	18.42
100	61.15	71.95	74.80	69.30	25.85	36.30	39.30	33.82	100	67.75	78.45	81.05	75.75	22.75	30.10	29.75	27.53
Average	40.48	47.43	48.70	45.54	19.05	24.53	27.27	23.62	Average	46.32	53.63	55.00	51.65	16.50	20.70	21.13	19.44
*SW**									*2WFE*								
20	22.55	25.75	23.15	23.82	12.60	14.20	15.75	14.18	20	47.35	65.35	74.65	62.45	9.05	9.90	9.30	9.42
50	45.00	47.55	49.55	47.37	18.20	22.80	25.85	22.28	50	46.10	63.45	72.70	60.75	14.30	17.90	17.10	16.43
100	66.65	73.80	75.55	72.00	23.85	37.35	39.95	33.72	100	46.55	65.20	75.55	62.43	27.95	28.45	31.20	29.20
Average	44.73	49.03	49.42	47.73	18.22	24.78	27.18	23.39	Average	46.67	64.67	74.30	61.88	17.10	18.75	19.20	18.35
CCEMG									*CCEP*								
20	5.95	8.15	8.15	7.42	10.50	10.65	10.40	10.52	20	7.80	7.85	8.00	7.88	9.30	10.25	10.00	9.85
50	5.75	5.70	6.30	5.92	18.10	20.60	22.30	20.33	50	5.35	5.65	6.35	5.78	17.15	20.20	21.60	19.65
100	5.05	6.45	4.65	5.38	32.25	36.70	45.40	38.12	100	5.25	5.55	5.55	5.45	29.30	34.10	40.10	34.50
Average	5.58	6.77	6.37	6.24	20.28	22.65	26.03	22.99	Average	6.13	6.35	6.63	6.37	18.58	21.52	23.90	21.33
CCEMGX									*CCEPX*								
20	4.35	6.70	6.95	6.00	10.90	10.45	10.55	10.63	20	5.90	6.75	6.80	6.48	9.30	10.05	10.90	10.08
50	5.90	5.00	6.00	5.63	16.50	21.55	22.40	20.15	50	5.05	5.10	5.70	5.28	16.85	20.65	21.55	19.68
100	4.45	6.30	4.55	5.10	32.95	36.25	44.80	38.00	100	4.80	5.25	5.30	5.12	29.70	33.60	39.25	34.18
Average	4.90	6.00	5.83	5.58	20.12	22.75	25.92	22.93	Average	5.25	5.70	5.93	5.63	18.62	21.43	23.90	21.32
IPCMG									*IPCP*								
20	5.05	6.40	6.75	6.07	11.10	11.75	10.65	11.17	20	10.20	11.05	11.00	10.75	8.10	9.80	8.65	8.85
50	6.00	5.45	5.55	5.67	17.85	21.85	22.60	20.77	50	8.05	7.70	8.55	8.10	13.75	13.85	13.85	13.82
100	4.80	5.95	4.95	5.23	35.65	37.95	43.90	39.17	100	7.25	8.80	7.90	7.98	20.20	19.95	24.25	21.47
Average	5.28	5.93	5.75	5.66	21.53	23.85	25.72	23.70	Average	8.50	9.18	9.15	8.94	14.02	14.53	15.58	14.71
PCMGX									*PCPX*								
20	5.85	6.50	6.50	6.28	8.95	11.00	10.10	10.02	20	5.90	6.30	6.35	6.18	8.85	11.20	10.50	10.18
50	5.55	5.50	5.40	5.48	14.00	18.20	23.05	18.42	50	5.55	4.50	5.10	5.05	13.30	19.75	22.45	18.50
100	5.45	5.65	5.05	5.38	25.00	34.00	40.40	33.13	100	5.05	5.45	5.30	5.27	25.85	31.70	38.00	31.85
Average	5.62	5.88	5.65	5.72	15.98	21.07	24.52	20.52	Average	5.50	5.42	5.58	5.50	16.00	20.88	23.65	20.18
PCMGX2S									*PCPX2S*								
20	5.40	6.75	6.80	6.32	9.65	11.10	10.50	10.42	20	7.00	7.80	7.65	7.48	8.70	10.35	10.05	9.70
50	5.55	5.25	5.95	5.58	16.80	21.20	23.30	20.43	50	5.45	5.70	6.30	5.82	16.45	20.65	21.10	19.40
100	4.95	5.85	4.65	5.15	29.65	35.80	44.30	36.58	100	5.20	5.70	5.30	5.40	28.60	33.95	40.50	34.35
Average	5.30	5.95	5.80	5.68	18.70	22.70	26.03	22.48	Average	5.88	6.40	6.42	6.23	17.92	21.65	23.88	21.15

Table A54: High Heterogeneity – DGP4, Case h: High Spatial Dependence & High Factor Dependence – SMA Errors

	Heterogeneous									*Homogeneous*							
	Bias (x 100)				RMSE (x 100)					Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
*MG**									*FE**								
20	35.72	36.29	34.43	35.48	44.28	42.72	39.33	42.11	20	43.19	45.17	43.68	44.01	51.65	51.41	48.75	50.60
50	37.23	35.66	34.70	35.87	42.63	38.59	37.03	39.42	50	44.77	45.17	44.29	44.75	50.69	48.49	46.88	48.69
100	35.88	35.75	35.28	35.63	39.62	37.69	36.70	38.01	100	44.24	45.02	45.17	44.81	49.07	47.34	46.85	47.75
Average	36.27	35.90	34.80	35.66	42.18	39.67	37.69	39.85	Average	44.07	45.12	44.38	44.52	50.47	49.08	47.49	49.01
*SW**									*2WFE*								
20	38.53	37.57	35.15	37.08	46.31	43.67	39.93	43.30	20	-0.30	0.27	-0.23	0.27	17.19	16.48	15.53	16.40
50	39.76	37.09	35.42	37.42	44.69	39.92	37.71	40.77	50	-0.04	-0.32	-0.30	0.22	11.32	10.03	9.89	10.41
100	38.69	37.09	36.05	37.28	42.37	38.98	37.46	39.60	100	-0.08	-0.28	0.14	0.17	7.65	7.14	7.16	7.32
Average	38.99	37.25	35.54	37.26	44.46	40.86	38.37	41.23	Average	0.14	0.29	0.23	0.22	12.05	11.22	10.86	11.38
CCEMG									*CCEP*								
20	-0.48	0.21	-0.31	0.33	14.50	13.13	12.53	13.39	20	-0.72	0.35	-0.28	0.45	15.80	14.14	13.21	14.38
50	0.35	-0.39	0.02	0.26	9.89	8.09	7.92	8.63	50	0.07	-0.27	-0.03	0.12	10.16	8.53	8.20	8.96
100	-0.09	-0.24	0.14	0.15	6.66	5.85	5.57	6.03	100	-0.08	-0.33	0.14	0.18	7.03	6.15	5.82	6.33
Average	0.31	0.28	0.16	0.25	10.35	9.02	8.68	9.35	Average	0.29	0.32	0.15	0.25	11.00	9.61	9.08	9.89
CCEMGX									*CCEPX*								
20	-0.37	0.26	-0.30	0.31	14.75	13.22	12.55	13.51	20	-0.72	0.33	-0.27	0.44	15.82	14.13	13.21	14.39
50	0.35	-0.40	0.03	0.26	10.04	8.12	7.94	8.70	50	0.05	-0.28	-0.02	0.12	10.19	8.53	8.20	8.98
100	-0.11	-0.25	0.13	0.16	6.69	5.86	5.58	6.04	100	-0.09	-0.33	0.13	0.18	7.04	6.15	5.82	6.33
Average	0.28	0.30	0.16	0.25	10.49	9.07	8.69	9.42	Average	0.29	0.31	0.14	0.25	11.02	9.60	9.08	9.90
IPCMG									*IPCP*								
20	-0.74	0.29	-0.35	0.46	15.02	13.04	12.42	13.50	20	-1.06	-0.48	-0.53	0.69	16.68	15.52	14.60	15.60
50	0.31	-0.38	0.03	0.24	9.75	8.02	7.87	8.55	50	-0.24	-0.69	-0.34	0.42	10.75	9.28	9.27	9.77
100	-0.07	-0.22	0.13	0.14	6.39	5.76	5.54	5.90	100	-0.44	-0.51	0.04	0.33	7.37	6.95	6.71	7.01
Average	0.37	0.30	0.17	0.28	10.39	8.94	8.61	9.31	Average	0.58	0.56	0.30	0.48	11.60	10.58	10.19	10.79
PCMGX									*PCPX*								
20	1.59	1.18	-0.11	0.96	22.79	16.90	13.70	17.79	20	1.21	0.96	-0.26	0.81	20.99	16.66	13.87	17.17
50	1.15	0.03	0.20	0.46	15.53	10.20	8.69	11.47	50	0.81	0.08	0.10	0.33	13.84	10.07	8.81	10.90
100	0.86	0.22	0.18	0.42	10.42	7.28	6.21	7.97	100	0.81	0.06	0.18	0.35	9.73	7.19	6.32	7.75
Average	1.20	0.48	0.16	0.61	16.25	11.46	9.53	12.41	Average	0.94	0.37	0.18	0.50	14.85	11.31	9.67	11.94
PCMGX2S									*PCPX2S*								
20	-0.26	0.44	-0.28	0.33	15.89	13.42	12.40	13.90	20	-0.45	0.35	-0.35	0.38	16.09	14.13	12.90	14.37
50	0.28	-0.32	0.08	0.23	10.61	8.14	7.90	8.88	50	0.01	-0.31	-0.04	0.12	10.57	8.55	8.17	9.10
100	-0.03	-0.22	0.15	0.13	6.96	5.85	5.56	6.12	100	-0.05	-0.31	0.15	0.17	7.18	6.17	5.77	6.38
Average	0.19	0.33	0.17	0.23	11.15	9.13	8.62	9.64	Average	0.17	0.33	0.18	0.23	11.28	9.62	8.95	9.95
	Size (x 100)				Size Adjusted Power (x 100)					Size (x 100)				Size Adjusted Power (x 100)			
*MG**									*FE**								
20	34.55	44.90	47.10	42.18	10.10	10.45	11.50	10.68	20	44.75	55.75	57.05	52.52	10.25	10.20	10.85	10.43
50	61.65	77.80	82.45	73.97	11.25	15.10	17.45	14.60	50	76.00	85.80	90.05	83.95	11.15	13.60	13.45	12.73
100	83.85	95.65	98.10	92.53	16.35	24.85	25.35	22.18	100	90.05	98.45	99.00	95.83	12.80	19.55	18.50	16.95
Average	60.02	72.78	75.88	69.56	12.57	16.80	18.10	15.82	Average	70.27	80.00	82.03	77.43	11.40	14.45	14.27	13.37
*SW**									*2WFE*								
20	40.85	47.40	48.70	45.65	9.85	10.65	11.45	10.65	20	46.50	63.70	73.95	61.38	9.00	9.55	9.45	9.33
50	70.75	80.90	84.10	78.58	12.20	14.35	17.45	14.67	50	45.20	62.90	72.50	60.20	14.30	17.30	15.95	15.85
100	89.25	97.05	98.40	94.90	16.30	25.15	25.05	22.17	100	45.15	63.35	75.40	61.30	25.70	26.65	31.15	27.83
Average	66.95	75.12	77.07	73.04	12.78	16.72	17.98	15.83	Average	45.62	63.32	73.95	60.96	16.33	17.83	18.85	17.67
CCEMG									*CCEP*								
20	5.95	7.90	8.05	7.30	11.20	10.75	9.85	10.60	20	7.80	8.05	8.30	8.05	9.10	10.45	10.20	9.92
50	5.75	5.60	6.15	5.83	17.75	21.15	22.00	20.30	50	5.10	5.65	6.30	5.68	17.10	20.85	21.10	19.68
100	4.95	6.40	4.80	5.38	32.50	35.25	44.70	37.48	100	5.20	5.45	5.50	5.38	29.60	34.05	39.70	34.45
Average	5.55	6.63	6.33	6.17	20.48	22.38	25.52	22.79	Average	6.03	6.38	6.70	6.37	18.60	21.78	23.67	21.35
CCEMGX									*CCEPX*								
20	4.50	6.45	6.95	5.97	10.55	10.30	10.50	10.45	20	5.45	6.60	6.75	6.27	9.15	10.65	10.35	10.05
50	5.60	5.05	6.05	5.57	16.95	20.95	22.75	20.22	50	4.85	5.00	5.75	5.20	16.90	20.80	21.80	19.83
100	4.60	6.30	4.75	5.22	32.55	35.65	44.40	37.53	100	4.65	5.15	5.20	5.00	29.70	33.55	39.15	34.13
Average	4.90	5.93	5.92	5.58	20.02	22.30	25.88	22.73	Average	4.98	5.58	5.90	5.49	18.58	21.67	23.77	21.34
IPCMG									*IPCP*								
20	5.10	6.45	6.85	6.13	10.55	11.40	10.60	10.85	20	8.15	10.05	9.75	9.32	8.80	9.75	10.35	9.63
50	6.00	5.25	5.55	5.60	17.05	21.45	22.60	20.37	50	6.85	6.10	7.40	6.78	16.10	18.10	15.75	16.65
100	4.70	5.80	4.90	5.13	35.00	37.15	44.10	38.75	100	6.45	7.20	7.10	6.92	26.00	26.00	32.95	28.32
Average	5.27	5.83	5.77	5.62	20.87	23.33	25.77	23.32	Average	7.15	7.78	8.08	7.67	16.97	17.95	19.68	18.20
PCMGX									*PCPX*								
20	5.55	6.45	6.10	6.03	8.15	10.35	10.45	9.65	20	5.50	6.00	6.00	5.83	7.85	9.85	10.25	9.32
50	5.55	5.40	5.20	5.38	10.60	14.70	20.15	15.15	50	5.55	4.95	5.00	5.17	11.30	14.90	20.15	15.45
100	5.30	5.15	4.70	5.05	18.65	28.05	35.95	27.55	100	5.15	5.10	5.25	5.17	20.85	27.05	33.60	27.17
Average	5.47	5.67	5.33	5.49	12.47	17.70	22.18	17.45	Average	5.40	5.35	5.42	5.39	13.33	17.27	21.33	17.31
PCMGX2S									*PCPX2S*								
20	5.35	6.40	6.70	6.15	9.30	11.50	10.50	10.43	20	6.45	7.70	7.45	7.20	8.25	11.35	10.20	9.93
50	5.60	5.35	6.10	5.68	15.05	21.00	23.60	19.88	50	5.50	5.25	6.15	5.63	15.90	20.60	20.60	19.03
100	5.00	5.75	4.60	5.12	29.05	35.80	44.15	36.33	100	4.95	5.60	5.35	5.30	28.80	33.75	41.00	34.52
Average	5.32	5.83	5.80	5.65	17.80	22.77	26.08	22.22	Average	5.63	6.18	6.32	6.04	17.65	21.90	23.93	21.16

Table A55: Partially Heterogeneous Estimators – Low Heterogeneity – DGP2, Case *a*: Low Spatial Dependence – SMA Errors

	K = 2								*K = 3*							
	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N \ *T*	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	-0.24	0.08	-0.03	0.12	12.34	10.40	10.41	11.05	-0.07	0.01	-0.09	0.06	11.97	10.15	9.98	10.70
50	0.09	0.15	0.26	0.17	7.47	6.52	6.39	6.79	0.16	0.21	0.18	0.18	7.39	6.33	6.02	6.58
100	0.12	0.02	-0.05	0.06	5.05	4.75	4.55	4.78	0.09	-0.01	-0.06	0.05	5.06	4.61	4.46	4.71
Average	0.15	0.08	0.11	0.12	8.29	7.22	7.11	7.54	0.11	0.08	0.11	0.10	8.14	7.03	6.82	7.33
C-Lasso CCE																
20	2.09	1.83	1.58	1.83	11.74	10.51	9.82	10.69	2.66	2.51	2.20	2.46	11.95	10.73	9.91	10.86
50	2.38	1.90	1.90	2.06	8.13	6.55	6.39	7.02	3.25	2.91	2.61	2.92	8.19	6.91	6.65	7.25
100	2.45	1.77	1.48	1.90	6.02	5.00	4.71	5.24	3.27	2.84	2.27	2.79	6.23	5.30	4.96	5.50
Average	2.31	1.83	1.65	1.93	8.63	7.35	6.97	7.65	3.06	2.75	2.36	2.72	8.79	7.65	7.17	7.87
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	35.20	38.20	42.60	38.67	9.40	11.20	10.20	10.27	39.00	46.70	48.60	44.77	8.40	9.80	9.30	9.17
50	26.40	36.10	41.40	34.63	17.30	16.50	16.30	16.70	29.60	41.70	48.10	39.80	21.70	19.70	14.50	18.63
100	20.80	31.70	40.10	30.87	41.70	39.40	34.30	38.47	21.70	36.80	44.70	34.40	31.30	31.60	25.30	29.40
Average	27.47	35.33	41.37	34.72	22.80	22.37	20.27	21.81	30.10	41.73	47.13	39.66	20.47	20.37	16.37	19.07
C-Lasso CCE																
20	18.00	20.80	19.70	19.50	12.70	13.10	13.40	13.07	31.10	35.40	35.70	34.07	9.10	11.00	11.20	10.43
50	13.80	15.40	15.60	14.93	18.20	20.30	25.70	21.40	24.80	27.10	26.10	26.00	17.00	20.30	19.80	19.03
100	14.80	14.10	12.60	13.83	28.90	39.80	39.50	36.07	22.50	24.80	22.80	23.37	30.80	34.30	35.40	33.50
Average	15.53	16.77	15.97	16.09	19.93	24.40	26.20	23.51	26.13	29.10	28.20	27.81	18.97	21.87	22.13	20.99

Table A56: Partially Heterogeneous Estimators – Low Heterogeneity – DGP2, Case *b*: High Spatial Dependence - SMA Errors

	K = 2								*K = 3*							
	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N \ *T*	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	-0.04	0.03	0.10	0.05	12.55	10.46	10.38	11.13	-0.16	0.03	0.01	0.06	12.39	10.21	10.05	10.88
50	0.11	0.16	0.18	0.15	7.68	6.53	6.46	6.89	0.10	0.22	0.27	0.20	7.52	6.29	6.07	6.63
100	0.11	0.03	-0.05	0.06	5.21	4.82	4.59	4.87	0.01	0.02	-0.06	0.03	5.22	4.66	4.44	4.78
Average	0.09	0.07	0.11	0.09	8.48	7.27	7.14	7.63	0.09	0.09	0.11	0.10	8.38	7.05	6.85	7.43
C-Lasso CCE																
20	2.16	1.59	1.44	1.73	12.23	10.52	9.89	10.88	2.72	2.23	2.18	2.37	12.27	10.74	10.06	11.02
50	2.39	1.79	1.94	2.04	8.20	6.59	6.37	7.05	3.21	3.03	2.74	2.99	8.34	7.03	6.72	7.36
100	2.44	1.84	1.52	1.93	6.20	5.06	4.77	5.34	3.31	2.92	2.33	2.85	6.35	5.41	5.02	5.59
Average	2.33	1.74	1.63	1.90	8.88	7.39	7.01	7.76	3.08	2.73	2.41	2.74	8.99	7.73	7.27	7.99
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	29.70	36.20	40.80	35.57	8.70	10.10	10.00	9.60	36.90	45.30	46.60	42.93	9.80	9.90	8.40	9.37
50	27.20	35.20	42.30	34.90	20.80	24.00	16.60	20.47	25.20	41.00	47.10	37.77	16.80	18.30	13.40	16.17
100	20.20	31.60	38.50	30.10	37.90	44.50	37.30	39.90	20.00	35.90	44.50	33.47	37.70	29.00	31.60	32.77
Average	25.70	34.33	40.53	33.52	22.47	26.20	21.30	23.32	27.37	40.73	46.07	38.06	21.43	19.07	17.80	19.43
C-Lasso CCE																
20	18.40	20.50	19.60	19.50	13.30	11.70	13.70	12.90	31.80	35.70	35.80	34.43	10.40	10.60	11.30	10.77
50	14.00	15.20	15.00	14.73	20.20	22.70	27.50	23.47	22.20	28.10	26.70	25.67	16.10	20.90	18.60	18.53
100	13.50	13.80	13.80	13.70	31.60	40.00	40.40	37.33	20.60	24.80	24.30	23.23	31.00	32.40	40.90	34.77
Average	15.30	16.50	16.13	15.98	21.70	24.80	27.20	24.57	24.87	29.53	28.93	27.78	19.17	21.30	23.60	21.36

Table A57: Partially Heterogeneous Estimators – Low Heterogeneity – DGP4, Case e: Low Spatial Dependence & Low Factor Dependence – SMA Errors

	$K = 2$								$K = 3$							
T	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.14	0.31	-0.17	0.21	12.34	10.67	10.18	11.07	0.12	0.55	-0.06	0.24	12.10	10.33	9.96	10.79
50	-0.26	-0.11	-0.39	0.26	7.29	6.72	6.64	6.89	-0.20	-0.18	-0.39	0.26	7.16	6.62	6.29	6.69
100	0.21	-0.18	-0.28	0.22	5.43	4.75	4.74	4.97	0.13	-0.10	-0.24	0.16	5.34	4.62	4.62	4.86
Average	0.20	0.20	0.28	0.23	8.35	7.38	7.19	7.64	0.15	0.28	0.23	0.22	8.20	7.19	6.96	7.45
C-Lasso CCE																
20	1.93	2.31	1.49	1.91	11.98	10.13	9.77	10.63	2.69	2.94	2.22	2.62	12.08	10.45	10.05	10.86
50	2.15	1.56	1.20	1.64	7.34	6.60	6.39	6.77	3.02	2.58	2.15	2.59	7.39	6.75	6.55	6.90
100	2.31	1.47	1.29	1.69	5.94	4.99	4.80	5.24	3.39	2.57	2.20	2.72	6.21	5.28	4.98	5.49
Average	2.13	1.78	1.33	1.75	8.42	7.24	6.99	7.55	3.03	2.70	2.19	2.64	8.56	7.49	7.19	7.75
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	31.20	33.70	38.90	34.60	11.80	10.30	9.30	10.47	38.10	40.60	43.60	40.77	8.40	11.60	10.00	10.00
50	22.70	29.70	33.60	28.67	23.60	19.60	20.50	21.23	27.30	34.30	37.10	32.90	16.70	19.20	14.50	16.80
100	22.10	31.10	30.30	27.83	37.80	39.50	36.40	37.90	26.20	31.40	34.80	30.80	31.20	29.50	39.70	33.47
Average	25.33	31.50	34.27	30.37	24.40	23.13	22.07	23.20	30.53	35.43	38.50	34.82	18.77	20.10	21.40	20.09
C-Lasso CCE																
20	20.30	21.90	18.80	20.33	12.10	15.50	10.80	12.80	32.50	38.60	34.90	35.33	10.50	9.30	10.60	10.13
50	13.50	11.90	14.20	13.20	17.40	20.60	18.60	18.87	24.20	26.00	27.50	25.90	19.60	19.10	17.10	18.60
100	13.80	14.70	13.60	14.03	31.20	32.90	38.20	34.10	23.30	26.50	26.30	25.37	28.00	28.10	30.70	28.93
Average	15.87	16.17	15.53	15.86	20.23	23.00	22.53	21.92	26.67	30.37	29.57	28.87	19.37	18.83	19.47	19.22

Table A58: Partially Heterogeneous Estimators – Low Heterogeneity – DGP4, Case f: Low Spatial Dependence & High Factor Dependence – SMA Errors

	$K = 2$								$K = 3$							
T	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.46	0.30	-0.19	0.32	13.13	11.33	10.88	11.78	0.14	0.37	-0.16	0.22	12.76	10.99	10.22	11.32
50	-0.23	-0.18	-0.29	0.24	7.76	7.17	6.91	7.28	-0.30	-0.19	-0.32	0.27	7.62	7.03	6.56	7.07
100	0.20	-0.20	-0.41	0.27	5.73	4.97	5.04	5.25	0.21	-0.27	-0.19	0.22	5.60	4.88	4.88	5.12
Average	0.30	0.23	0.30	0.27	8.88	7.82	7.61	8.10	0.22	0.28	0.22	0.24	8.66	7.63	7.22	7.84
C-Lasso CCE																
20	2.17	2.35	1.70	2.07	12.44	10.50	10.15	11.03	2.54	3.23	2.47	2.75	12.37	10.70	10.30	11.12
50	2.16	1.62	1.29	1.69	7.60	6.87	6.53	7.00	3.09	2.84	2.29	2.74	7.56	7.11	6.72	7.13
100	2.47	1.58	1.38	1.81	6.18	5.22	4.92	5.44	3.54	2.73	2.36	2.88	6.31	5.46	5.18	5.65
Average	2.27	1.85	1.45	1.86	8.74	7.53	7.20	7.82	3.06	2.93	2.38	2.79	8.74	7.76	7.40	7.97
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	32.60	29.40	33.10	31.70	12.20	9.60	12.30	11.37	36.50	36.30	41.50	38.10	8.50	8.10	8.30	8.30
50	20.30	23.70	27.40	23.80	22.00	22.10	21.50	21.87	22.50	28.30	32.70	27.83	15.60	20.00	19.50	18.37
100	19.10	24.20	24.40	22.57	41.80	40.30	40.00	40.70	21.00	24.40	27.70	24.37	33.80	40.30	37.40	37.17
Average	24.00	25.77	28.30	26.02	25.33	24.00	24.60	24.64	26.67	29.67	33.97	30.10	19.30	22.80	21.73	21.28
C-Lasso CCE																
20	21.60	21.70	20.00	21.10	10.30	14.80	9.40	11.50	33.10	36.20	37.70	35.67	9.70	8.60	12.80	10.37
50	15.20	12.00	12.10	13.10	18.60	19.10	18.50	18.73	24.60	25.30	27.60	25.83	19.10	21.20	17.70	19.33
100	12.60	14.70	12.40	13.23	30.90	31.10	37.30	33.10	22.20	25.10	24.40	23.90	24.60	27.00	24.10	25.23
Average	16.47	16.13	14.83	15.81	19.93	21.67	21.73	21.11	26.63	28.87	29.90	28.47	17.80	18.93	18.20	18.31

Table A59: Partially Heterogeneous Estimators – Low Heterogeneity – DGP4, Case g: High Spatial Dependence & Low Factor Dependence – SMA Errors

	$K = 2$								$K = 3$							
	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	-0.07	-0.42	0.35	0.28	11.80	11.17	10.44	11.14	-0.37	-0.52	0.28	0.39	11.51	10.92	10.16	10.86
50	0.30	0.07	-0.32	0.23	7.59	6.82	6.71	7.04	0.23	0.09	-0.20	0.18	7.39	6.67	6.40	6.82
100	-0.25	0.21	-0.04	0.17	5.27	5.01	4.70	4.99	-0.19	0.29	-0.04	0.17	5.01	4.84	4.57	4.81
Average	0.21	0.23	0.24	0.23	8.22	7.67	7.28	7.72	0.26	0.30	0.17	0.25	7.97	7.48	7.04	7.50
C-Lasso CCE																
20	2.16	1.65	2.06	1.96	11.89	10.64	10.39	10.97	2.60	2.39	2.92	2.64	11.85	10.67	10.39	10.97
50	2.27	1.80	1.41	1.82	8.00	6.92	6.77	7.23	3.24	2.79	2.25	2.76	8.19	7.23	7.00	7.47
100	1.89	2.06	1.60	1.85	5.75	5.34	4.95	5.35	2.87	3.24	2.51	2.87	5.93	5.79	5.16	5.63
Average	2.11	1.84	1.69	1.88	8.54	7.63	7.37	7.85	2.90	2.81	2.56	2.76	8.66	7.90	7.52	8.02
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	27.80	35.00	36.70	33.17	8.90	12.20	10.80	10.63	34.80	38.70	42.90	38.80	8.10	9.40	9.80	9.10
50	24.10	31.20	33.80	29.70	16.90	19.70	23.20	19.93	28.10	34.60	39.00	33.90	21.30	19.70	19.00	20.00
100	20.20	27.40	30.80	26.13	36.10	41.50	41.10	39.57	20.40	29.90	34.60	28.30	34.60	36.70	33.50	34.93
Average	24.03	31.20	33.77	29.67	20.63	24.47	25.03	23.38	27.77	34.40	38.83	33.67	21.33	21.93	20.77	21.34
C-Lasso CCE																
20	18.60	19.90	21.80	20.10	12.50	12.60	10.60	11.90	32.60	35.40	36.10	34.70	10.50	9.80	10.30	10.20
50	15.80	14.70	15.80	15.43	15.70	22.80	21.70	20.07	26.40	32.50	28.70	29.20	16.50	12.70	15.60	14.93
100	13.10	14.60	14.50	14.07	31.60	32.30	37.00	33.63	18.70	26.20	26.60	23.83	28.30	31.30	32.70	30.77
Average	15.83	16.40	17.37	16.53	19.93	22.57	23.10	21.87	25.90	31.37	30.47	29.24	18.43	17.93	19.53	18.63

Table A60: Partially Heterogeneous Estimators – Low Heterogeneity – DGP4, Case h: High Spatial Dependence & High Factor Dependence – SMA Errors

	$K = 2$								$K = 3$							
	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	0.05	-0.32	0.43	0.26	12.71	11.87	11.03	11.87	-0.23	-0.46	0.28	0.32	12.38	11.21	10.65	11.41
50	0.21	0.27	-0.43	0.30	8.13	7.31	7.09	7.51	0.22	0.18	-0.23	0.21	8.03	7.08	6.92	7.34
100	-0.18	0.30	-0.08	0.18	5.55	5.30	5.05	5.30	-0.23	0.24	-0.02	0.16	5.36	5.09	4.94	5.13
Average	0.15	0.29	0.31	0.25	8.80	8.16	7.72	8.23	0.23	0.29	0.18	0.23	8.59	7.79	7.50	7.96
C-Lasso CCE																
20	2.18	1.82	2.08	2.03	12.27	11.14	10.79	11.40	2.59	2.62	3.15	2.79	12.15	11.01	10.87	11.34
50	2.44	1.76	1.48	1.89	8.47	7.09	7.00	7.52	3.34	2.92	2.37	2.88	8.52	7.37	7.23	7.71
100	2.04	2.06	1.64	1.91	6.05	5.52	5.03	5.53	3.09	3.41	2.63	3.04	6.14	6.07	5.38	5.86
Average	2.22	1.88	1.74	1.95	8.93	7.91	7.61	8.15	3.00	2.98	2.72	2.90	8.94	8.15	7.83	8.30
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	24.60	33.00	34.10	30.57	9.60	13.80	9.30	10.90	30.90	38.80	43.00	37.57	9.10	8.50	7.90	8.50
50	21.70	27.50	28.80	26.00	20.80	18.60	19.10	19.50	26.60	29.10	33.90	29.87	19.70	22.10	17.80	19.87
100	16.50	23.90	25.70	22.03	37.20	39.60	37.60	38.13	16.20	26.40	27.20	23.27	38.30	35.80	41.00	38.37
Average	20.93	28.13	29.53	26.20	22.53	24.00	22.00	22.84	24.57	31.43	34.70	30.23	22.37	22.13	22.23	22.24
C-Lasso CCE																
20	17.70	19.80	21.50	19.67	10.50	12.10	11.40	11.33	32.50	34.90	35.10	34.17	10.10	9.20	10.30	9.87
50	15.00	15.60	16.30	15.63	17.00	18.50	20.90	18.80	25.20	30.00	28.20	27.80	19.10	17.30	18.20	18.20
100	13.20	13.90	12.40	13.17	30.60	31.80	34.90	32.43	19.30	27.10	26.10	24.17	29.90	26.50	29.80	28.73
Average	15.30	16.43	16.73	16.16	19.37	20.80	22.40	20.86	25.67	30.67	29.80	28.71	19.70	17.67	19.43	18.93

Table A61: Partially Heterogeneous Estimators – High Heterogeneity – DGP2, Case *a*: Low Spatial Dependence – SMA Errors

	K = 2								*K = 3*							
T	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	-0.28	-0.06	-0.02	0.12	16.23	14.40	14.47	15.03	-0.37	-0.07	-0.14	0.20	15.75	13.91	13.81	14.49
50	0.21	0.21	0.34	0.25	10.02	8.93	8.93	9.29	0.22	0.30	0.28	0.27	9.68	8.74	8.32	8.91
100	0.21	0.08	-0.05	0.11	6.88	6.58	6.33	6.60	0.06	0.03	-0.05	0.05	6.56	6.37	6.23	6.39
Average	0.23	0.12	0.14	0.16	11.05	9.97	9.91	10.31	0.22	0.13	0.16	0.17	10.66	9.67	9.45	9.93
C-Lasso CCE																
20	3.50	3.38	3.10	3.33	15.41	14.62	14.07	14.70	3.20	4.09	4.37	3.89	15.10	14.79	14.42	14.77
50	3.76	3.39	3.59	3.58	10.68	9.40	9.52	9.87	4.35	5.16	5.44	4.98	10.67	10.07	10.25	10.33
100	3.91	3.17	3.04	3.37	8.35	7.40	7.21	7.65	4.19	4.93	5.06	4.73	7.89	7.88	8.09	7.95
Average	3.72	3.32	3.25	3.43	11.48	10.47	10.27	10.74	3.91	4.72	4.96	4.53	11.22	10.91	10.92	11.02
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	37.60	38.40	45.80	40.60	10.10	8.90	9.00	9.33	40.60	46.70	50.20	45.83	7.70	8.40	9.50	8.53
50	31.80	38.60	45.00	38.47	14.20	13.00	13.10	13.43	33.30	45.70	47.40	42.13	15.40	11.10	16.20	14.23
100	25.40	35.90	41.00	34.10	25.90	19.40	19.70	21.67	30.40	42.40	49.00	40.60	23.60	21.80	15.70	20.37
Average	31.60	37.63	43.93	37.72	16.73	13.77	13.93	14.81	34.77	44.93	48.87	42.86	15.57	13.77	13.80	14.38
C-Lasso CCE																
20	17.60	19.60	17.60	18.27	10.50	9.50	10.70	10.23	28.10	31.00	28.50	29.20	9.00	10.70	11.00	10.23
50	13.20	15.10	16.10	14.80	13.80	15.40	18.90	16.03	20.60	25.70	26.10	24.13	13.20	15.40	18.90	15.83
100	13.70	14.90	16.10	14.90	20.90	27.90	25.70	24.83	18.20	24.00	26.80	23.00	25.10	23.90	27.80	25.60
Average	14.83	16.53	16.60	15.99	15.07	17.60	18.43	17.03	22.30	26.90	27.13	25.44	15.77	16.67	19.23	17.22

Table A62: Partially Heterogeneous Estimators – High Heterogeneity – DGP2, Case *b*: High Spatial Dependence – SMA Errors

	K = 2								*K = 3*							
T	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	-0.14	-0.09	0.11	0.11	16.34	14.37	14.46	15.06	-0.18	-0.04	-0.16	0.13	16.21	14.01	13.75	14.66
50	0.09	0.17	0.32	0.19	10.18	8.97	8.92	9.36	0.07	0.28	0.32	0.23	9.92	8.69	8.35	8.99
100	0.21	-0.05	-0.26	0.17	6.98	6.32	6.05	6.45	0.09	-0.09	-0.19	0.12	6.71	5.91	5.94	6.19
Average	0.15	0.10	0.23	0.16	11.17	9.89	9.81	10.29	0.11	0.14	0.22	0.16	10.94	9.54	9.35	9.94
C-Lasso CCE																
20	3.39	3.04	2.95	3.13	15.77	14.56	14.12	14.81	3.20	3.64	4.16	3.66	15.63	14.62	14.37	14.87
50	3.65	3.45	3.59	3.56	10.60	9.48	9.46	9.84	4.12	5.16	5.49	4.92	10.50	9.96	10.33	10.26
100	3.84	3.58	2.71	3.38	8.26	7.50	6.94	7.57	4.09	5.21	4.83	4.71	7.90	7.88	7.77	7.85
Average	3.63	3.36	3.08	3.36	11.54	10.51	10.17	10.74	3.80	4.67	4.83	4.43	11.34	10.82	10.82	10.99
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	35.40	39.60	44.20	39.73	9.00	9.70	10.10	9.60	39.30	46.80	49.40	45.17	7.10	8.80	7.60	7.83
50	28.80	37.00	43.20	36.33	13.70	15.30	12.20	13.73	34.60	45.90	47.80	42.77	13.80	11.40	14.90	13.37
100	25.40	33.30	40.90	33.20	25.60	23.80	22.80	24.07	26.60	38.70	47.40	37.57	21.50	20.00	23.60	21.70
Average	29.87	36.63	42.77	36.42	16.10	16.27	15.03	15.80	33.50	43.80	48.20	41.83	14.13	13.40	15.37	14.30
C-Lasso CCE																
20	17.80	18.40	17.10	17.77	12.70	10.70	10.10	11.17	27.20	31.00	28.80	29.00	6.80	9.60	10.60	9.00
50	13.70	15.20	16.40	15.10	14.80	15.80	17.40	16.00	20.20	24.50	26.80	23.83	14.80	15.00	17.30	15.70
100	12.60	16.70	16.70	15.33	19.40	23.30	27.20	23.30	17.80	26.50	30.50	24.93	28.20	26.30	31.30	28.60
Average	14.70	16.77	16.73	16.07	15.63	16.60	18.23	16.82	21.73	27.33	28.70	25.92	16.60	16.97	19.73	17.77

Table A63: Partially Heterogeneous Estimators – High Heterogeneity – DGP4, Case e: Low Spatial Dependence & Low Factor Dependence – SMA Errors

	K = 2								*K = 3*							
	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	-0.14	-0.47	0.58	0.40	15.33	15.01	14.27	14.87	-0.40	-0.45	0.56	0.47	15.05	14.50	13.78	14.44
50	0.26	0.09	-0.40	0.25	10.08	9.29	9.19	9.52	0.30	0.15	-0.31	0.25	9.55	8.95	8.96	9.15
100	-0.11	0.32	-0.04	0.16	6.76	6.75	6.65	6.72	-0.11	0.42	0.03	0.19	6.49	6.51	6.39	6.46
Average	0.17	0.29	0.34	0.27	10.72	10.35	10.04	10.37	0.27	0.34	0.30	0.30	10.36	9.99	9.71	10.02
C-Lasso CCE																
20	3.30	3.10	3.80	3.40	15.17	14.81	14.72	14.90	3.12	3.73	4.82	3.89	14.72	14.43	14.50	14.55
50	3.53	3.04	2.78	3.12	10.53	9.81	9.77	10.03	4.16	4.63	4.71	4.50	10.37	10.14	10.29	10.27
100	3.01	3.45	2.96	3.14	7.90	7.81	7.36	7.69	3.97	5.37	5.08	4.80	7.56	8.35	8.13	8.01
Average	3.28	3.20	3.18	3.22	11.20	10.81	10.61	10.87	3.75	4.57	4.87	4.40	10.88	10.97	10.97	10.94
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	32.50	38.70	38.90	36.70	7.80	7.70	10.60	8.70	38.60	42.10	45.90	42.20	7.70	9.10	9.20	8.67
50	30.20	33.40	36.00	33.20	15.00	12.50	14.30	13.93	32.40	38.00	41.60	37.33	15.50	13.30	14.30	14.37
100	25.90	31.90	35.20	31.00	25.50	19.30	23.80	22.87	24.80	32.70	36.90	31.47	20.60	25.80	20.60	22.33
Average	29.53	34.67	36.70	33.63	16.10	13.17	16.23	15.17	31.93	37.60	41.47	37.00	14.60	16.07	14.70	15.12
C-Lasso CCE																
20	15.40	17.50	19.50	17.47	9.60	9.60	9.10	9.43	28.10	30.40	32.60	30.37	8.70	9.40	9.40	9.17
50	14.40	14.90	16.10	15.13	16.40	18.00	15.00	16.47	25.10	26.10	27.70	26.30	15.00	14.20	15.20	14.80
100	13.40	14.50	13.30	13.73	25.30	18.80	23.90	22.67	19.90	24.80	27.40	24.03	20.90	22.80	19.70	21.13
Average	14.40	15.63	16.30	15.44	17.10	15.47	16.00	16.19	24.37	27.10	29.23	26.90	14.87	15.47	14.77	15.03

Table A64: Partially Heterogeneous Estimators – High Heterogeneity – DGP4, Case f: Low Spatial Dependence & High Factor Dependence – SMA Errors

	K = 2								*K = 3*							
	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
N \ T	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	-0.22	-0.54	0.54	0.44	16.04	15.42	14.59	15.35	-0.22	-0.52	0.43	0.39	15.32	15.02	14.12	14.82
50	0.34	0.13	-0.50	0.32	10.34	9.51	9.48	9.78	0.16	0.31	-0.37	0.28	10.11	9.19	9.19	9.49
100	-0.28	0.34	0.00	0.21	7.03	7.03	6.77	6.94	-0.19	0.42	0.02	0.21	6.69	6.73	6.50	6.64
Average	0.28	0.34	0.35	0.32	11.14	10.65	10.28	10.69	0.19	0.42	0.27	0.29	10.71	10.31	9.94	10.32
C-Lasso CCE																
20	3.36	3.22	3.72	3.43	15.55	15.19	14.97	15.24	3.11	3.70	4.88	3.90	15.24	14.92	14.84	15.00
50	3.62	3.07	2.80	3.16	10.70	9.84	10.02	10.19	4.20	4.56	4.70	4.49	10.59	10.14	10.38	10.37
100	3.17	3.50	2.99	3.22	8.03	7.97	7.42	7.81	4.12	5.37	5.20	4.90	7.82	8.49	8.26	8.19
Average	3.38	3.26	3.17	3.27	11.43	11.00	10.80	11.08	3.81	4.54	4.93	4.43	11.22	11.18	11.16	11.19
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	30.80	35.00	35.80	33.87	7.60	10.10	9.40	9.03	33.10	39.70	43.60	38.80	7.60	8.30	7.90	7.93
50	26.50	32.40	33.60	30.83	15.30	13.60	13.10	14.00	31.50	32.30	36.60	33.47	16.20	12.40	13.90	14.17
100	22.30	28.40	31.70	27.47	23.70	20.40	21.80	21.97	22.40	30.20	31.80	28.13	24.00	21.50	22.40	22.63
Average	26.53	31.93	33.70	30.72	15.53	14.70	14.77	15.00	29.00	34.07	37.33	33.47	15.93	14.07	14.73	14.91
C-Lasso CCE																
20	15.10	19.30	18.90	17.77	9.10	10.50	9.70	9.77	27.50	30.80	30.90	29.73	7.00	8.90	11.90	9.27
50	14.00	14.20	15.10	14.43	14.90	15.80	16.00	15.57	23.30	25.40	26.90	25.20	13.70	13.70	14.00	13.80
100	12.70	14.20	13.30	13.40	22.90	22.00	23.30	22.73	18.70	25.50	27.50	23.90	18.10	24.60	22.10	21.60
Average	13.93	15.90	15.77	15.20	15.63	16.10	16.33	16.02	23.17	27.23	28.43	26.28	12.93	15.73	16.00	14.89

Table A65: Partially Heterogeneous Estimators – High Heterogeneity – DGP4, Case g: High Spatial Dependence & Low Factor Dependence – SMA Errors

	K = 2								*K = 3*							
T / N	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	-0.17	-0.36	0.60	0.38	15.40	15.03	14.21	14.88	0.02	-0.39	0.51	0.31	15.08	14.54	13.77	14.46
50	0.30	0.05	-0.36	0.24	10.04	9.29	9.16	9.50	0.21	0.10	-0.27	0.20	9.65	8.97	9.00	9.21
100	-0.12	0.31	0.01	0.14	6.79	6.76	6.64	6.73	-0.30	0.40	0.03	0.25	6.56	6.51	6.43	6.50
Average	0.20	0.24	0.32	0.25	10.74	10.36	10.00	10.37	0.18	0.30	0.27	0.25	10.43	10.01	9.73	10.06
C-Lasso CCE																
20	3.26	3.16	3.73	3.38	15.52	14.71	14.69	14.98	3.10	3.54	4.85	3.83	15.02	14.48	14.56	14.69
50	3.47	3.08	2.80	3.11	10.67	9.89	9.84	10.13	3.97	4.52	4.74	4.41	10.49	10.04	10.36	10.30
100	3.08	3.55	3.00	3.21	7.96	7.89	7.37	7.74	3.88	5.41	5.13	4.81	7.69	8.38	8.18	8.08
Average	3.27	3.26	3.18	3.24	11.38	10.83	10.63	10.95	3.65	4.49	4.90	4.35	11.06	10.97	11.03	11.02
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	30.10	39.70	37.40	35.73	8.90	8.60	9.60	9.03	38.40	40.40	45.80	41.53	7.90	9.80	8.20	8.63
50	28.90	34.40	36.00	33.10	14.90	14.40	15.70	15.00	34.30	39.10	41.80	38.40	14.50	15.60	13.40	14.50
100	25.70	30.80	36.00	30.83	22.60	21.10	19.60	21.10	25.80	35.50	35.70	32.33	21.10	24.00	24.10	23.07
Average	28.23	34.97	36.47	33.22	15.47	14.70	14.97	15.04	32.83	38.33	41.10	37.42	14.50	16.47	15.23	15.40
C-Lasso CCE																
20	15.40	18.30	20.00	17.90	9.50	10.50	10.30	10.10	27.30	29.90	33.20	30.13	9.60	8.40	8.50	8.83
50	15.60	14.80	15.20	15.20	15.60	17.50	16.90	16.67	24.40	26.20	27.10	25.90	14.50	13.80	16.00	14.77
100	13.30	14.60	13.60	13.83	22.80	23.30	25.00	23.70	18.40	24.30	28.50	23.73	23.80	22.90	20.40	22.37
Average	14.77	15.90	16.27	15.64	15.97	17.10	17.40	16.82	23.37	26.80	29.60	26.59	15.97	15.03	14.97	15.32

Table A66: Partially Heterogeneous Estimators – High Heterogeneity – DGP4, Case h: High Spatial Dependence & High Factor Dependence – SMA Errors

	K = 2								*K = 3*							
T / N	Bias (x 100)				RMSE (x 100)				Bias (x 100)				RMSE (x 100)			
	20	50	100	Average	20	50	100	Average	20	50	100	Average	20	50	100	Average
GFE																
20	-0.12	-0.43	0.45	0.33	16.25	15.47	14.55	15.42	-0.16	-0.54	0.64	0.44	15.43	15.04	14.29	14.92
50	0.44	0.11	-0.45	0.33	10.41	9.51	9.50	9.81	0.16	0.18	-0.30	0.22	10.21	9.27	9.07	9.52
100	-0.31	0.30	-0.01	0.21	7.08	7.01	6.59	6.89	-0.33	0.37	-0.09	0.26	6.70	6.77	6.47	6.65
Average	0.29	0.28	0.30	0.29	11.25	10.66	10.21	10.71	0.21	0.36	0.34	0.31	10.78	10.36	9.94	10.36
C-Lasso CCE																
20	3.25	3.17	3.69	3.37	15.74	15.23	14.98	15.32	2.77	3.77	5.11	3.88	15.25	14.92	15.03	15.07
50	3.55	2.99	2.84	3.13	10.85	9.86	10.04	10.25	4.01	4.52	4.79	4.44	10.62	10.21	10.42	10.41
100	3.19	3.56	3.02	3.26	8.10	8.02	7.49	7.87	4.03	5.37	5.26	4.89	7.80	8.47	8.29	8.19
Average	3.33	3.24	3.18	3.25	11.56	11.04	10.83	11.15	3.60	4.55	5.05	4.40	11.22	11.20	11.25	11.22
	Size (x 100)				Size Adjusted Power (x 100)				Size (x 100)				Size Adjusted Power (x 100)			
GFE																
20	27.30	36.70	35.80	33.27	8.10	9.80	9.70	9.20	34.90	39.50	41.40	38.60	9.40	8.50	8.30	8.73
50	26.00	30.20	31.20	29.13	12.80	14.80	13.60	13.73	30.50	32.00	35.90	32.80	15.20	16.30	13.90	15.13
100	20.50	29.00	30.70	26.73	20.20	23.30	25.10	22.87	22.40	32.00	32.20	28.87	24.30	26.90	22.50	24.57
Average	24.60	31.97	32.57	29.71	13.70	15.97	16.13	15.27	29.27	34.50	36.50	33.42	16.30	17.23	14.90	16.14
C-Lasso CCE																
20	16.20	18.10	19.80	18.03	8.50	11.00	10.10	9.87	28.90	28.40	30.50	29.27	8.10	8.70	10.00	8.93
50	14.10	14.50	15.10	14.57	13.70	14.40	16.20	14.77	22.10	26.70	24.90	24.57	15.60	14.30	13.20	14.37
100	13.60	13.90	14.60	14.03	19.60	20.60	22.60	20.93	18.00	24.70	29.20	23.97	20.70	25.50	25.70	23.97
Average	14.63	15.50	16.50	15.54	13.93	15.33	16.30	15.19	23.00	26.60	28.20	25.93	14.80	16.17	16.30	15.76

Table A67: Forecasting Accuracy Measures, Low Heterogeneity – DGP2, Case a: Low Spatial Dependence – SMA Errors

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	1.137	0.972	0.943	1.017	0.448	0.418	0.360	0.409	20	1.184	1.079	1.068	1.110	0.466	0.463	0.408	0.446
50	1.108	1.018	0.996	1.040	0.410	0.385	0.396	0.397	50	1.163	1.128	1.117	1.136	0.433	0.428	0.445	0.435
100	1.091	1.001	0.993	1.028	0.426	0.376	0.386	0.396	100	1.146	1.113	1.115	1.125	0.448	0.419	0.434	0.434
Average	1.112	0.997	0.977	1.029	0.428	0.393	0.380	0.400	Average	1.164	1.107	1.100	1.124	0.449	0.437	0.429	0.438
Ind. GLS									*2WFE*								
20	1.106	0.967	0.943	1.005	0.435	0.416	0.360	0.404	20	1.268	1.170	1.164	1.200	0.498	0.498	0.442	0.479
50	1.075	1.014	0.995	1.028	0.399	0.383	0.396	0.392	50	1.220	1.197	1.198	1.205	0.453	0.453	0.476	0.460
100	1.056	0.997	0.992	1.015	0.412	0.374	0.385	0.391	100	1.205	1.185	1.192	1.194	0.468	0.444	0.462	0.458
Average	1.079	0.993	0.976	1.016	0.415	0.391	0.380	0.396	Average	1.231	1.184	1.184	1.200	0.473	0.465	0.460	0.466
Ind. CCE									*CCEP*								
20	1.212	1.003	0.958	1.058	0.478	0.432	0.365	0.425	20	1.238	1.096	1.072	1.135	0.488	0.472	0.410	0.456
50	1.175	1.051	1.012	1.079	0.436	0.397	0.403	0.412	50	1.216	1.158	1.129	1.168	0.453	0.439	0.450	0.447
100	1.155	1.036	1.009	1.067	0.451	0.389	0.392	0.411	100	1.194	1.146	1.130	1.157	0.467	0.432	0.441	0.446
Average	1.181	1.030	0.993	1.068	0.455	0.406	0.387	0.416	Average	1.216	1.133	1.111	1.153	0.469	0.447	0.433	0.450
Ind. CCEX									*CCEPX*								
20	1.220	1.005	0.958	1.061	0.481	0.433	0.365	0.426	20	1.238	1.096	1.072	1.136	0.488	0.472	0.410	0.456
50	1.180	1.052	1.012	1.081	0.437	0.398	0.403	0.413	50	1.216	1.158	1.129	1.168	0.453	0.439	0.450	0.447
100	1.160	1.037	1.009	1.069	0.453	0.389	0.392	0.411	100	1.194	1.146	1.130	1.157	0.467	0.432	0.441	0.446
Average	1.186	1.031	0.993	1.070	0.457	0.407	0.387	0.417	Average	1.216	1.133	1.111	1.153	0.469	0.447	0.433	0.450
Ind. IPC									*IPCP*								
20	1.260	1.010	0.960	1.077	0.497	0.436	0.366	0.433	20	1.239	1.097	1.072	1.136	0.489	0.472	0.410	0.457
50	1.191	1.053	1.013	1.086	0.441	0.398	0.403	0.414	50	1.216	1.158	1.129	1.168	0.453	0.439	0.450	0.447
100	1.159	1.036	1.009	1.068	0.453	0.389	0.392	0.411	100	1.195	1.146	1.130	1.157	0.467	0.432	0.441	0.446
Average	1.203	1.033	0.994	1.077	0.464	0.408	0.387	0.419	Average	1.216	1.134	1.111	1.154	0.470	0.448	0.433	0.450
Ind. PCX									*PCPX*								
20	1.240	1.010	0.960	1.070	0.489	0.435	0.366	0.430	20	1.238	1.097	1.072	1.136	0.488	0.472	0.410	0.457
50	1.201	1.055	1.013	1.090	0.446	0.399	0.403	0.416	50	1.216	1.158	1.129	1.168	0.453	0.439	0.450	0.448
100	1.188	1.041	1.011	1.080	0.464	0.391	0.393	0.416	100	1.195	1.146	1.130	1.157	0.467	0.432	0.441	0.446
Average	1.210	1.035	0.995	1.080	0.466	0.408	0.387	0.421	Average	1.216	1.133	1.111	1.154	0.470	0.448	0.433	0.450
Ind. PCX2S									*PCPX2S*								
20	1.267	1.013	0.961	1.080	0.500	0.436	0.366	0.434	20	1.240	1.097	1.072	1.136	0.489	0.472	0.410	0.457
50	1.225	1.058	1.014	1.099	0.455	0.400	0.404	0.419	50	1.217	1.158	1.129	1.168	0.453	0.439	0.450	0.448
100	1.212	1.043	1.011	1.089	0.474	0.392	0.393	0.419	100	1.195	1.146	1.130	1.157	0.467	0.432	0.441	0.446
Average	1.235	1.038	0.995	1.089	0.476	0.409	0.388	0.424	Average	1.217	1.134	1.111	1.154	0.470	0.448	0.433	0.450

Table A68: Forecasting Accuracy Measures, Low Heterogeneity – DGP2, Case *b*: High Spatial Dependence - SMA Errors

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	1.253	1.072	1.037	1.121	0.482	0.451	0.389	0.441	20	1.281	1.167	1.150	1.199	0.493	0.489	0.432	0.471
50	1.207	1.110	1.083	1.133	0.441	0.413	0.423	0.426	50	1.244	1.209	1.194	1.216	0.456	0.450	0.467	0.458
100	1.183	1.084	1.076	1.115	0.454	0.401	0.411	0.422	100	1.222	1.184	1.189	1.198	0.469	0.439	0.455	0.454
Average	1.214	1.089	1.065	1.123	0.459	0.422	0.408	0.429	Average	1.249	1.187	1.178	1.204	0.473	0.460	0.451	0.461
Ind. GLS									*2WFE*								
20	1.215	1.067	1.036	1.106	0.467	0.449	0.388	0.435	20	1.385	1.279	1.270	1.311	0.532	0.533	0.474	0.513
50	1.169	1.105	1.082	1.119	0.427	0.411	0.423	0.420	50	1.307	1.285	1.283	1.292	0.478	0.477	0.501	0.485
100	1.142	1.079	1.075	1.099	0.438	0.399	0.411	0.416	100	1.279	1.258	1.268	1.268	0.489	0.465	0.483	0.479
Average	1.175	1.084	1.064	1.108	0.444	0.420	0.407	0.424	Average	1.323	1.274	1.274	1.290	0.500	0.492	0.486	0.493
Ind. CCE									*CCEP*								
20	1.328	1.106	1.052	1.162	0.512	0.465	0.395	0.457	20	1.342	1.189	1.157	1.229	0.517	0.500	0.434	0.484
50	1.277	1.145	1.100	1.174	0.467	0.426	0.430	0.441	50	1.303	1.242	1.209	1.251	0.478	0.463	0.473	0.471
100	1.251	1.121	1.094	1.155	0.480	0.415	0.418	0.438	100	1.274	1.221	1.206	1.233	0.489	0.453	0.462	0.468
Average	1.286	1.124	1.082	1.164	0.487	0.436	0.414	0.445	Average	1.306	1.217	1.190	1.238	0.495	0.472	0.456	0.474
Ind. CCEX									*CCEPX*								
20	1.344	1.110	1.053	1.169	0.518	0.467	0.395	0.460	20	1.342	1.189	1.157	1.230	0.517	0.500	0.434	0.484
50	1.285	1.147	1.101	1.178	0.470	0.427	0.430	0.442	50	1.303	1.242	1.209	1.251	0.478	0.463	0.473	0.471
100	1.257	1.123	1.094	1.158	0.483	0.416	0.418	0.439	100	1.274	1.221	1.206	1.233	0.489	0.453	0.462	0.468
Average	1.296	1.127	1.083	1.168	0.490	0.436	0.414	0.447	Average	1.306	1.217	1.190	1.238	0.495	0.472	0.456	0.474
Ind. IPC									*IPCP*								
20	1.337	1.104	1.052	1.164	0.515	0.465	0.394	0.458	20	1.342	1.189	1.157	1.229	0.517	0.500	0.434	0.484
50	1.277	1.145	1.100	1.174	0.467	0.426	0.430	0.441	50	1.303	1.242	1.209	1.251	0.478	0.463	0.473	0.471
100	1.245	1.121	1.094	1.153	0.478	0.415	0.418	0.437	100	1.274	1.221	1.206	1.233	0.489	0.453	0.462	0.468
Average	1.287	1.123	1.082	1.164	0.487	0.435	0.414	0.445	Average	1.306	1.217	1.190	1.238	0.495	0.472	0.456	0.474
Ind. PCX									*PCPX*								
20	1.366	1.114	1.055	1.179	0.527	0.469	0.395	0.464	20	1.343	1.189	1.157	1.230	0.518	0.500	0.434	0.484
50	1.309	1.151	1.102	1.187	0.479	0.428	0.431	0.446	50	1.303	1.242	1.209	1.251	0.478	0.463	0.473	0.471
100	1.288	1.127	1.096	1.170	0.495	0.417	0.419	0.444	100	1.274	1.221	1.206	1.234	0.490	0.453	0.462	0.468
Average	1.321	1.131	1.084	1.179	0.500	0.438	0.415	0.451	Average	1.307	1.217	1.191	1.238	0.495	0.472	0.456	0.475
Ind. PCX2S									*PCPX2S*								
20	1.374	1.112	1.054	1.180	0.530	0.468	0.395	0.464	20	1.344	1.189	1.157	1.230	0.518	0.500	0.434	0.484
50	1.324	1.152	1.102	1.193	0.485	0.428	0.431	0.448	50	1.303	1.242	1.209	1.251	0.478	0.463	0.473	0.471
100	1.309	1.129	1.096	1.178	0.503	0.418	0.419	0.446	100	1.274	1.221	1.206	1.234	0.490	0.453	0.462	0.468
Average	1.336	1.131	1.084	1.184	0.506	0.438	0.415	0.453	Average	1.307	1.217	1.190	1.238	0.495	0.472	0.456	0.475

Table A69: Forecasting Accuracy Measures, Low Heterogeneity – DGP4, Case *e*: Low Spatial Dependence & Low Factor Dependence - SMA Errors

	Heterogeneous									*Homogeneous*							
	RMSE				Theil's U					RMSE				Theil's U			
T / N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	1.919	1.724	1.671	1.771	0.572	0.547	0.504	0.541	20	2.051	1.936	1.905	1.964	0.610	0.613	0.572	0.598
50	1.892	1.746	1.690	1.776	0.560	0.516	0.475	0.517	50	2.030	1.961	1.928	1.973	0.599	0.579	0.540	0.573
100	1.901	1.718	1.679	1.766	0.533	0.496	0.491	0.507	100	2.045	1.937	1.914	1.965	0.571	0.558	0.558	0.563
Average	1.904	1.729	1.680	1.771	0.555	0.520	0.490	0.521	Average	2.042	1.944	1.916	1.967	0.593	0.583	0.557	0.578
Ind. GLS									*2WFE*								
20	1.872	1.715	1.669	1.752	0.557	0.544	0.503	0.535	20	2.339	2.266	2.285	2.297	0.693	0.716	0.686	0.699
50	1.840	1.736	1.688	1.755	0.544	0.513	0.474	0.510	50	2.304	2.315	2.308	2.309	0.677	0.680	0.647	0.668
100	1.845	1.708	1.676	1.743	0.516	0.493	0.490	0.500	100	2.326	2.291	2.285	2.301	0.647	0.658	0.664	0.656
Average	1.852	1.720	1.678	1.750	0.539	0.517	0.489	0.515	Average	2.323	2.291	2.293	2.302	0.672	0.685	0.666	0.674
Ind. CCE									*CCEP*								
20	1.430	1.101	1.023	1.185	0.431	0.353	0.314	0.366	20	1.462	1.202	1.137	1.267	0.439	0.385	0.349	0.391
50	1.386	1.106	1.032	1.174	0.414	0.331	0.293	0.346	50	1.422	1.213	1.151	1.262	0.423	0.363	0.327	0.371
100	1.402	1.065	1.027	1.165	0.396	0.312	0.305	0.338	100	1.430	1.179	1.149	1.253	0.403	0.345	0.341	0.363
Average	1.406	1.091	1.027	1.175	0.414	0.332	0.304	0.350	Average	1.438	1.198	1.146	1.260	0.422	0.364	0.339	0.375
Ind. CCEX									*CCEPX*								
20	1.439	1.104	1.024	1.189	0.434	0.353	0.315	0.367	20	1.462	1.202	1.137	1.267	0.439	0.385	0.349	0.391
50	1.390	1.107	1.032	1.176	0.415	0.331	0.293	0.347	50	1.422	1.213	1.151	1.262	0.423	0.363	0.327	0.371
100	1.404	1.066	1.027	1.166	0.397	0.312	0.305	0.338	100	1.430	1.179	1.149	1.253	0.403	0.345	0.341	0.363
Average	1.411	1.092	1.028	1.177	0.415	0.332	0.304	0.351	Average	1.438	1.198	1.146	1.260	0.422	0.364	0.339	0.375
Ind. IPC									*IPCP*								
20	1.444	1.101	1.021	1.189	0.434	0.352	0.314	0.367	20	1.465	1.204	1.138	1.269	0.440	0.386	0.349	0.392
50	1.368	1.101	1.029	1.166	0.409	0.329	0.293	0.343	50	1.422	1.213	1.151	1.262	0.423	0.363	0.327	0.371
100	1.373	1.059	1.024	1.152	0.388	0.310	0.304	0.334	100	1.431	1.179	1.149	1.253	0.403	0.345	0.341	0.363
Average	1.395	1.087	1.025	1.169	0.410	0.331	0.303	0.348	Average	1.439	1.199	1.146	1.261	0.422	0.365	0.339	0.375
Ind. PCX									*PCPX*								
20	1.578	1.162	1.047	1.262	0.474	0.372	0.321	0.389	20	1.466	1.204	1.137	1.269	0.440	0.386	0.349	0.392
50	1.523	1.159	1.056	1.246	0.453	0.346	0.300	0.367	50	1.424	1.213	1.151	1.263	0.424	0.363	0.327	0.371
100	1.542	1.120	1.052	1.238	0.435	0.328	0.312	0.358	100	1.431	1.179	1.149	1.253	0.404	0.345	0.341	0.363
Average	1.547	1.147	1.052	1.249	0.454	0.349	0.311	0.371	Average	1.441	1.199	1.146	1.262	0.423	0.365	0.339	0.376
Ind. PCX2S									*PCPX2S*								
20	1.482	1.109	1.023	1.205	0.446	0.355	0.314	0.372	20	1.463	1.202	1.136	1.267	0.439	0.385	0.349	0.391
50	1.416	1.109	1.032	1.186	0.423	0.332	0.293	0.349	50	1.422	1.213	1.150	1.262	0.423	0.363	0.327	0.371
100	1.428	1.068	1.027	1.175	0.404	0.313	0.305	0.341	100	1.431	1.179	1.149	1.253	0.403	0.345	0.341	0.363
Average	1.442	1.095	1.027	1.188	0.424	0.333	0.304	0.354	Average	1.439	1.198	1.145	1.261	0.422	0.364	0.339	0.375

Table A70: Forecasting Accuracy Measures, Low Heterogeneity – DGP4, Case f: Low Spatial Dependence & High Factor Dependence - SMA Errors

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	3.181	2.881	2.790	2.950	0.757	0.713	0.665	0.712	20	3.281	3.108	3.055	3.148	0.778	0.768	0.727	0.757
50	3.153	2.895	2.804	2.951	0.748	0.686	0.637	0.690	50	3.251	3.124	3.080	3.152	0.768	0.739	0.699	0.735
100	3.162	2.865	2.773	2.933	0.721	0.670	0.649	0.680	100	3.272	3.099	3.041	3.137	0.743	0.723	0.710	0.725
Average	3.165	2.880	2.789	2.945	0.742	0.690	0.651	0.694	Average	3.268	3.110	3.059	3.146	0.763	0.743	0.712	0.739
Ind. GLS									*2WFE*								
20	3.092	2.861	2.785	2.913	0.734	0.708	0.664	0.702	20	3.875	3.818	3.861	3.851	0.919	0.948	0.926	0.931
50	3.056	2.874	2.799	2.910	0.723	0.680	0.636	0.680	50	3.850	3.873	3.878	3.867	0.911	0.919	0.887	0.906
100	3.058	2.845	2.766	2.890	0.696	0.665	0.647	0.669	100	3.890	3.854	3.825	3.856	0.884	0.903	0.896	0.894
Average	3.069	2.860	2.783	2.904	0.718	0.684	0.649	0.684	Average	3.871	3.848	3.855	3.858	0.905	0.923	0.903	0.910
Ind. CCE									*CCEP*								
20	1.796	1.253	1.122	1.390	0.432	0.317	0.277	0.342	20	1.817	1.339	1.224	1.460	0.436	0.339	0.302	0.359
50	1.726	1.209	1.083	1.339	0.413	0.293	0.253	0.320	50	1.752	1.306	1.195	1.418	0.418	0.317	0.279	0.338
100	1.733	1.151	1.060	1.315	0.399	0.276	0.256	0.310	100	1.755	1.257	1.178	1.397	0.403	0.301	0.284	0.329
Average	1.752	1.204	1.088	1.348	0.415	0.295	0.262	0.324	Average	1.775	1.300	1.199	1.425	0.419	0.319	0.289	0.342
Ind. CCEX									*CCEPX*								
20	1.812	1.260	1.125	1.399	0.436	0.318	0.278	0.344	20	1.817	1.339	1.224	1.460	0.436	0.339	0.302	0.359
50	1.734	1.212	1.084	1.343	0.415	0.294	0.253	0.321	50	1.752	1.306	1.195	1.418	0.418	0.317	0.279	0.338
100	1.738	1.153	1.061	1.317	0.400	0.276	0.256	0.311	100	1.755	1.257	1.178	1.397	0.403	0.301	0.284	0.329
Average	1.761	1.208	1.090	1.353	0.417	0.296	0.262	0.325	Average	1.775	1.300	1.199	1.425	0.419	0.319	0.289	0.342
Ind. IPC									*IPCP*								
20	1.806	1.248	1.116	1.390	0.434	0.315	0.276	0.342	20	1.819	1.340	1.225	1.461	0.436	0.339	0.302	0.359
50	1.707	1.202	1.078	1.329	0.408	0.291	0.252	0.317	50	1.752	1.306	1.196	1.418	0.418	0.317	0.279	0.338
100	1.707	1.144	1.057	1.303	0.393	0.274	0.255	0.307	100	1.755	1.257	1.179	1.397	0.403	0.301	0.284	0.329
Average	1.740	1.198	1.084	1.341	0.412	0.294	0.261	0.322	Average	1.775	1.301	1.200	1.425	0.419	0.319	0.289	0.342
Ind. PCX									*PCPX*								
20	2.188	1.434	1.200	1.607	0.525	0.361	0.295	0.394	20	1.831	1.346	1.226	1.468	0.439	0.341	0.302	0.361
50	2.112	1.373	1.164	1.550	0.505	0.332	0.271	0.369	50	1.758	1.308	1.196	1.421	0.420	0.317	0.280	0.339
100	2.132	1.321	1.144	1.532	0.490	0.316	0.275	0.360	100	1.758	1.258	1.179	1.398	0.404	0.301	0.284	0.330
Average	2.144	1.376	1.169	1.563	0.507	0.336	0.281	0.375	Average	1.783	1.304	1.200	1.429	0.421	0.320	0.289	0.343
Ind. PCX2S									*PCPX2S*								
20	1.859	1.266	1.121	1.415	0.447	0.320	0.277	0.348	20	1.818	1.339	1.223	1.460	0.436	0.338	0.302	0.359
50	1.761	1.213	1.082	1.352	0.421	0.294	0.253	0.323	50	1.752	1.306	1.195	1.418	0.418	0.317	0.279	0.338
100	1.765	1.155	1.061	1.327	0.406	0.277	0.256	0.313	100	1.755	1.257	1.178	1.397	0.403	0.301	0.284	0.329
Average	1.795	1.211	1.088	1.365	0.425	0.297	0.262	0.328	Average	1.775	1.300	1.199	1.425	0.419	0.319	0.288	0.342

Table A71: Forecasting Accuracy Measures, Low Heterogeneity – DGP4, Case g: High Spatial Dependence & Low Factor Dependence - SMA Errors

	Heterogeneous									*Homogeneous*							
T / N	RMSE				Theil's U					RMSE				Theil's U			
	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	1.990	1.780	1.730	1.834	0.587	0.559	0.517	0.554	20	2.109	1.984	1.956	2.016	0.620	0.622	0.582	0.608
50	1.953	1.804	1.748	1.835	0.573	0.528	0.487	0.529	50	2.080	2.010	1.978	2.023	0.608	0.588	0.550	0.582
100	1.959	1.768	1.733	1.820	0.545	0.507	0.502	0.518	100	2.092	1.980	1.961	2.011	0.580	0.566	0.567	0.571
Average	1.968	1.784	1.737	1.829	0.568	0.531	0.502	0.534	Average	2.094	1.991	1.965	2.017	0.603	0.592	0.566	0.587
Ind. GLS									*2WFE*								
20	1.940	1.770	1.728	1.813	0.571	0.556	0.516	0.548	20	2.402	2.321	2.343	2.355	0.705	0.726	0.697	0.709
50	1.899	1.793	1.745	1.812	0.556	0.525	0.486	0.522	50	2.351	2.361	2.358	2.356	0.684	0.688	0.655	0.676
100	1.900	1.758	1.730	1.796	0.528	0.504	0.501	0.511	100	2.369	2.331	2.329	2.343	0.653	0.665	0.671	0.663
Average	1.913	1.774	1.734	1.807	0.552	0.528	0.501	0.527	Average	2.374	2.338	2.343	2.351	0.681	0.693	0.674	0.683
Ind. CCE									*CCEP*								
20	1.534	1.189	1.115	1.280	0.457	0.377	0.339	0.391	20	1.552	1.282	1.220	1.351	0.461	0.407	0.371	0.413
50	1.481	1.196	1.122	1.267	0.438	0.354	0.316	0.369	50	1.500	1.293	1.231	1.341	0.442	0.383	0.347	0.391
100	1.494	1.147	1.114	1.252	0.419	0.333	0.327	0.360	100	1.504	1.251	1.226	1.327	0.421	0.363	0.360	0.381
Average	1.503	1.178	1.117	1.266	0.438	0.355	0.328	0.373	Average	1.519	1.275	1.226	1.340	0.441	0.384	0.359	0.395
Ind. CCEX									*CCEPX*								
20	1.550	1.194	1.117	1.287	0.462	0.379	0.340	0.393	20	1.552	1.282	1.220	1.351	0.461	0.407	0.371	0.413
50	1.489	1.198	1.123	1.270	0.440	0.355	0.316	0.370	50	1.500	1.293	1.231	1.341	0.442	0.383	0.347	0.391
100	1.498	1.148	1.114	1.254	0.420	0.334	0.328	0.360	100	1.504	1.251	1.226	1.327	0.421	0.363	0.360	0.381
Average	1.512	1.180	1.118	1.270	0.441	0.356	0.328	0.375	Average	1.519	1.275	1.226	1.340	0.441	0.384	0.359	0.395
Ind. IPC									*IPCP*								
20	1.526	1.189	1.116	1.277	0.454	0.377	0.339	0.390	20	1.554	1.283	1.222	1.353	0.461	0.407	0.371	0.413
50	1.456	1.192	1.121	1.256	0.431	0.353	0.316	0.366	50	1.500	1.293	1.232	1.342	0.442	0.383	0.347	0.391
100	1.460	1.141	1.111	1.237	0.409	0.332	0.327	0.356	100	1.504	1.251	1.227	1.327	0.421	0.363	0.361	0.381
Average	1.481	1.174	1.116	1.257	0.431	0.354	0.327	0.371	Average	1.520	1.276	1.227	1.341	0.441	0.384	0.360	0.395
Ind. PCX									*PCPX*								
20	1.681	1.249	1.138	1.356	0.499	0.395	0.346	0.413	20	1.557	1.284	1.221	1.354	0.462	0.407	0.371	0.413
50	1.612	1.247	1.146	1.335	0.476	0.369	0.323	0.389	50	1.502	1.293	1.232	1.342	0.443	0.383	0.347	0.391
100	1.627	1.199	1.137	1.321	0.455	0.348	0.334	0.379	100	1.505	1.251	1.226	1.327	0.421	0.363	0.361	0.382
Average	1.640	1.231	1.140	1.337	0.477	0.371	0.334	0.394	Average	1.521	1.276	1.226	1.341	0.442	0.385	0.359	0.395
Ind. PCX2S									*PCPX2S*								
20	1.583	1.197	1.115	1.298	0.471	0.379	0.339	0.396	20	1.554	1.282	1.220	1.352	0.461	0.407	0.370	0.413
50	1.511	1.200	1.123	1.278	0.447	0.355	0.316	0.373	50	1.500	1.293	1.231	1.341	0.442	0.383	0.347	0.391
100	1.521	1.150	1.115	1.262	0.427	0.334	0.328	0.363	100	1.504	1.251	1.226	1.327	0.421	0.363	0.360	0.381
Average	1.539	1.182	1.117	1.279	0.448	0.356	0.328	0.377	Average	1.519	1.275	1.226	1.340	0.441	0.384	0.359	0.395

Table A72: Forecasting Accuracy Measures, Low Heterogeneity – DGP4, Case h: High Spatial Dependence & High Factor Dependence - SMA Errors

	Heterogeneous									*Homogeneous*							
T / N	RMSE				Theil's U					RMSE				Theil's U			
	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	3.225	2.915	2.826	2.989	0.762	0.717	0.670	0.717	20	3.317	3.138	3.087	3.181	0.781	0.771	0.730	0.761
50	3.191	2.931	2.839	2.987	0.753	0.690	0.642	0.695	50	3.283	3.156	3.111	3.183	0.771	0.742	0.702	0.738
100	3.197	2.896	2.806	2.967	0.726	0.674	0.653	0.685	100	3.303	3.126	3.071	3.166	0.747	0.726	0.713	0.729
Average	3.204	2.914	2.824	2.981	0.747	0.694	0.655	0.699	Average	3.301	3.140	3.090	3.177	0.766	0.746	0.715	0.743
Ind. GLS									*2WFE*								
20	3.133	2.895	2.821	2.950	0.739	0.712	0.669	0.706	20	3.914	3.850	3.896	3.887	0.923	0.951	0.929	0.934
50	3.092	2.910	2.834	2.946	0.728	0.685	0.641	0.684	50	3.878	3.900	3.909	3.896	0.913	0.920	0.890	0.908
100	3.092	2.875	2.799	2.922	0.700	0.669	0.651	0.673	100	3.916	3.878	3.851	3.882	0.885	0.904	0.898	0.896
Average	3.106	2.893	2.818	2.939	0.722	0.688	0.654	0.688	Average	3.903	3.876	3.885	3.888	0.907	0.925	0.905	0.912
Ind. CCE									*CCEP*								
20	1.882	1.332	1.207	1.473	0.450	0.335	0.296	0.360	20	1.892	1.411	1.302	1.535	0.451	0.355	0.319	0.375
50	1.806	1.292	1.169	1.423	0.430	0.312	0.272	0.338	50	1.818	1.381	1.273	1.491	0.432	0.333	0.296	0.354
100	1.811	1.228	1.145	1.395	0.415	0.293	0.275	0.328	100	1.818	1.324	1.254	1.465	0.415	0.316	0.301	0.344
Average	1.833	1.284	1.174	1.430	0.432	0.313	0.281	0.342	Average	1.843	1.372	1.276	1.497	0.433	0.335	0.305	0.358
Ind. CCEX									*CCEPX*								
20	1.904	1.340	1.210	1.485	0.455	0.337	0.297	0.363	20	1.892	1.411	1.302	1.535	0.451	0.355	0.319	0.375
50	1.817	1.296	1.171	1.428	0.433	0.313	0.272	0.339	50	1.819	1.381	1.273	1.491	0.432	0.333	0.296	0.354
100	1.817	1.230	1.146	1.397	0.417	0.293	0.275	0.328	100	1.818	1.324	1.254	1.465	0.415	0.316	0.301	0.344
Average	1.846	1.289	1.176	1.437	0.435	0.314	0.282	0.344	Average	1.843	1.372	1.276	1.497	0.433	0.335	0.305	0.358
Ind. IPC									*IPCP*								
20	1.882	1.328	1.202	1.470	0.449	0.334	0.295	0.360	20	1.894	1.412	1.303	1.536	0.451	0.355	0.320	0.375
50	1.785	1.286	1.166	1.412	0.425	0.310	0.271	0.335	50	1.819	1.381	1.274	1.491	0.432	0.333	0.296	0.354
100	1.782	1.221	1.141	1.382	0.409	0.291	0.274	0.325	100	1.818	1.325	1.254	1.466	0.415	0.316	0.301	0.344
Average	1.816	1.278	1.170	1.421	0.428	0.312	0.280	0.340	Average	1.844	1.373	1.277	1.498	0.433	0.335	0.306	0.358
Ind. PCX									*PCPX*								
20	2.266	1.506	1.281	1.684	0.540	0.377	0.314	0.410	20	1.906	1.418	1.304	1.543	0.455	0.357	0.320	0.377
50	2.180	1.450	1.246	1.625	0.519	0.349	0.289	0.386	50	1.825	1.383	1.274	1.494	0.433	0.334	0.296	0.354
100	2.197	1.390	1.223	1.603	0.503	0.331	0.293	0.375	100	1.821	1.326	1.254	1.467	0.416	0.316	0.301	0.344
Average	2.214	1.449	1.250	1.638	0.520	0.352	0.299	0.390	Average	1.851	1.376	1.277	1.501	0.435	0.336	0.306	0.359
Ind. PCX2S									*PCPX2S*								
20	1.944	1.344	1.206	1.498	0.464	0.338	0.296	0.366	20	1.893	1.411	1.301	1.535	0.451	0.355	0.319	0.375
50	1.842	1.297	1.170	1.436	0.439	0.313	0.272	0.341	50	1.819	1.381	1.273	1.491	0.432	0.333	0.296	0.354
100	1.844	1.232	1.145	1.407	0.423	0.294	0.275	0.331	100	1.818	1.324	1.254	1.465	0.415	0.316	0.301	0.344
Average	1.877	1.291	1.174	1.447	0.442	0.315	0.281	0.346	Average	1.843	1.372	1.276	1.497	0.433	0.335	0.305	0.358

Table A73: Forecasting Accuracy Measures, High Heterogeneity – DGP2, Case a: Low Spatial Dependence – SMA Errors

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	1.137	0.972	0.943	1.017	0.451	0.416	0.363	0.410	20	1.297	1.190	1.179	1.222	0.514	0.507	0.455	0.492
50	1.108	1.018	0.996	1.040	0.413	0.387	0.397	0.399	50	1.281	1.241	1.227	1.250	0.482	0.475	0.490	0.482
100	1.091	1.001	0.993	1.028	0.428	0.377	0.387	0.397	100	1.267	1.226	1.226	1.240	0.497	0.464	0.480	0.480
Average	1.112	0.997	0.977	1.029	0.431	0.394	0.382	0.402	Average	1.282	1.219	1.211	1.237	0.498	0.482	0.475	0.485
Ind. GLS									*2WFE*								
20	1.117	0.969	0.943	1.010	0.442	0.415	0.363	0.407	20	1.440	1.327	1.323	1.363	0.569	0.560	0.507	0.545
50	1.087	1.015	0.995	1.032	0.406	0.386	0.397	0.396	50	1.392	1.357	1.358	1.369	0.521	0.517	0.541	0.526
100	1.068	0.999	0.992	1.020	0.419	0.376	0.387	0.394	100	1.381	1.352	1.354	1.362	0.539	0.508	0.526	0.525
Average	1.091	0.994	0.977	1.021	0.422	0.393	0.382	0.399	Average	1.404	1.345	1.345	1.365	0.543	0.529	0.525	0.532
Ind. CCE									*CCEP*								
20	1.213	1.004	0.958	1.058	0.482	0.430	0.369	0.427	20	1.342	1.196	1.176	1.238	0.533	0.511	0.454	0.499
50	1.176	1.051	1.012	1.080	0.439	0.400	0.404	0.414	50	1.332	1.267	1.237	1.278	0.501	0.485	0.494	0.493
100	1.156	1.036	1.009	1.067	0.454	0.391	0.393	0.413	100	1.314	1.258	1.240	1.271	0.516	0.476	0.486	0.493
Average	1.182	1.030	0.993	1.068	0.458	0.407	0.389	0.418	Average	1.329	1.240	1.218	1.262	0.517	0.491	0.478	0.495
Ind. CCEX									*CCEPX*								
20	1.220	1.005	0.958	1.061	0.484	0.431	0.369	0.428	20	1.342	1.196	1.176	1.238	0.533	0.511	0.454	0.499
50	1.180	1.052	1.012	1.081	0.441	0.400	0.404	0.415	50	1.331	1.267	1.237	1.278	0.501	0.485	0.494	0.493
100	1.160	1.037	1.009	1.069	0.455	0.391	0.393	0.413	100	1.314	1.258	1.240	1.271	0.516	0.476	0.486	0.493
Average	1.186	1.031	0.993	1.070	0.460	0.407	0.389	0.419	Average	1.329	1.240	1.218	1.262	0.517	0.491	0.478	0.495
Ind. IPC									*IPCP*								
20	1.260	1.010	0.960	1.077	0.500	0.433	0.370	0.434	20	1.344	1.197	1.177	1.239	0.534	0.511	0.455	0.500
50	1.191	1.053	1.013	1.086	0.444	0.401	0.404	0.416	50	1.332	1.267	1.237	1.279	0.501	0.485	0.494	0.493
100	1.159	1.036	1.009	1.068	0.455	0.391	0.393	0.413	100	1.314	1.258	1.240	1.271	0.516	0.476	0.486	0.493
Average	1.203	1.033	0.994	1.077	0.466	0.408	0.389	0.421	Average	1.330	1.241	1.218	1.263	0.517	0.491	0.478	0.495
Ind. PCX									*PCPX*								
20	1.240	1.010	0.960	1.070	0.493	0.433	0.369	0.432	20	1.343	1.196	1.176	1.238	0.533	0.511	0.454	0.499
50	1.201	1.055	1.013	1.090	0.449	0.402	0.404	0.418	50	1.332	1.267	1.237	1.279	0.501	0.485	0.494	0.493
100	1.188	1.041	1.011	1.080	0.466	0.393	0.394	0.418	100	1.315	1.258	1.240	1.271	0.516	0.476	0.486	0.493
Average	1.210	1.035	0.995	1.080	0.469	0.409	0.389	0.422	Average	1.330	1.240	1.218	1.263	0.517	0.491	0.478	0.495
Ind. PCX2S									*PCPX2S*								
20	1.267	1.013	0.961	1.080	0.504	0.434	0.370	0.436	20	1.344	1.196	1.176	1.239	0.534	0.511	0.455	0.500
50	1.225	1.058	1.014	1.099	0.458	0.403	0.405	0.422	50	1.332	1.267	1.237	1.279	0.501	0.485	0.494	0.494
100	1.212	1.043	1.011	1.089	0.476	0.394	0.394	0.421	100	1.315	1.258	1.240	1.271	0.517	0.476	0.486	0.493
Average	1.235	1.038	0.995	1.089	0.479	0.410	0.390	0.426	Average	1.330	1.240	1.218	1.263	0.517	0.491	0.478	0.495

Table A74: Forecasting Accuracy Measures, High Heterogeneity – DGP2, Case *b*: High Spatial Dependence - SMA Errors

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	1.253	1.072	1.037	1.121	0.485	0.448	0.392	0.442	20	1.388	1.271	1.256	1.305	0.537	0.529	0.475	0.514
50	1.207	1.110	1.083	1.133	0.444	0.415	0.424	0.427	50	1.356	1.315	1.299	1.324	0.501	0.494	0.509	0.501
100	1.183	1.084	1.076	1.115	0.456	0.402	0.412	0.423	100	1.336	1.293	1.295	1.308	0.515	0.481	0.497	0.498
Average	1.214	1.089	1.065	1.123	0.461	0.422	0.409	0.431	Average	1.360	1.293	1.283	1.312	0.518	0.501	0.494	0.504
Ind. GLS									*2WFE*								
20	1.228	1.069	1.036	1.111	0.475	0.447	0.391	0.438	20	1.546	1.426	1.419	1.464	0.597	0.589	0.533	0.573
50	1.181	1.107	1.082	1.124	0.434	0.414	0.423	0.424	50	1.470	1.436	1.436	1.447	0.542	0.537	0.561	0.546
100	1.156	1.081	1.076	1.104	0.445	0.401	0.412	0.419	100	1.448	1.418	1.423	1.430	0.555	0.525	0.543	0.541
Average	1.188	1.086	1.065	1.113	0.451	0.421	0.409	0.427	Average	1.488	1.427	1.426	1.447	0.565	0.550	0.546	0.554
Ind. CCE									*CCEP*								
20	1.330	1.107	1.053	1.163	0.515	0.463	0.398	0.459	20	1.440	1.282	1.254	1.326	0.558	0.535	0.475	0.523
50	1.278	1.146	1.100	1.175	0.470	0.428	0.431	0.443	50	1.412	1.345	1.311	1.356	0.522	0.505	0.513	0.514
100	1.252	1.121	1.094	1.156	0.482	0.416	0.419	0.439	100	1.388	1.327	1.311	1.342	0.535	0.494	0.504	0.511
Average	1.286	1.125	1.082	1.164	0.489	0.436	0.416	0.447	Average	1.413	1.318	1.292	1.341	0.538	0.511	0.497	0.516
Ind. CCEX									*CCEPX*								
20	1.344	1.110	1.053	1.169	0.521	0.464	0.398	0.461	20	1.441	1.283	1.255	1.326	0.558	0.535	0.475	0.523
50	1.285	1.147	1.101	1.178	0.473	0.429	0.431	0.444	50	1.412	1.345	1.311	1.356	0.522	0.505	0.513	0.514
100	1.257	1.123	1.094	1.158	0.485	0.417	0.419	0.440	100	1.388	1.327	1.311	1.342	0.535	0.494	0.504	0.511
Average	1.296	1.127	1.083	1.168	0.493	0.437	0.416	0.448	Average	1.413	1.318	1.292	1.341	0.539	0.511	0.497	0.516
Ind. IPC									*IPCP*								
20	1.337	1.104	1.052	1.164	0.518	0.462	0.397	0.459	20	1.441	1.283	1.255	1.326	0.558	0.535	0.475	0.523
50	1.277	1.145	1.100	1.174	0.470	0.428	0.431	0.443	50	1.412	1.345	1.311	1.356	0.523	0.505	0.513	0.514
100	1.245	1.121	1.094	1.153	0.480	0.416	0.419	0.438	100	1.388	1.327	1.310	1.342	0.535	0.494	0.504	0.511
Average	1.287	1.123	1.082	1.164	0.489	0.435	0.416	0.447	Average	1.414	1.318	1.292	1.341	0.539	0.511	0.497	0.516
Ind. PCX									*PCPX*								
20	1.366	1.114	1.055	1.179	0.530	0.466	0.398	0.465	20	1.441	1.283	1.254	1.326	0.558	0.535	0.475	0.523
50	1.309	1.151	1.102	1.187	0.482	0.430	0.431	0.448	50	1.413	1.345	1.311	1.356	0.523	0.505	0.513	0.514
100	1.288	1.127	1.096	1.170	0.496	0.418	0.420	0.445	100	1.388	1.327	1.311	1.342	0.535	0.494	0.504	0.511
Average	1.321	1.131	1.084	1.179	0.503	0.438	0.416	0.453	Average	1.414	1.318	1.292	1.341	0.539	0.511	0.497	0.516
Ind. PCX2S									*PCPX2S*								
20	1.374	1.112	1.054	1.180	0.533	0.465	0.398	0.465	20	1.442	1.283	1.254	1.326	0.559	0.535	0.475	0.523
50	1.324	1.152	1.102	1.193	0.488	0.431	0.431	0.450	50	1.413	1.345	1.311	1.356	0.523	0.505	0.513	0.514
100	1.309	1.129	1.096	1.178	0.505	0.419	0.420	0.448	100	1.388	1.327	1.311	1.342	0.535	0.494	0.504	0.511
Average	1.336	1.131	1.084	1.184	0.508	0.438	0.416	0.454	Average	1.414	1.318	1.292	1.342	0.539	0.511	0.497	0.516

Table A75: Forecasting Accuracy Measures, High Heterogeneity – DGP4, Case e: Low Spatial Dependence & Low Factor Dependence - SMA Errors

	Heterogeneous									*Homogeneous*							
	RMSE				Theil's U					RMSE				Theil's U			
N \ T	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	1.919	1.724	1.671	1.771	0.572	0.544	0.501	0.539	20	2.197	2.077	2.043	2.106	0.654	0.653	0.608	0.638
50	1.892	1.746	1.690	1.776	0.559	0.515	0.475	0.516	50	2.180	2.105	2.068	2.118	0.641	0.619	0.579	0.613
100	1.901	1.718	1.679	1.766	0.534	0.496	0.490	0.507	100	2.198	2.082	2.056	2.112	0.614	0.599	0.598	0.604
Average	1.904	1.729	1.680	1.771	0.555	0.518	0.489	0.521	Average	2.192	2.088	2.056	2.112	0.636	0.623	0.595	0.618
Ind. GLS									*2WFE*								
20	1.882	1.717	1.670	1.757	0.561	0.542	0.501	0.534	20	2.514	2.415	2.437	2.455	0.744	0.756	0.724	0.741
50	1.852	1.739	1.689	1.760	0.547	0.513	0.474	0.511	50	2.475	2.483	2.469	2.476	0.724	0.725	0.690	0.713
100	1.857	1.711	1.677	1.748	0.521	0.494	0.489	0.501	100	2.498	2.456	2.450	2.468	0.694	0.703	0.709	0.702
Average	1.864	1.723	1.678	1.755	0.543	0.516	0.488	0.516	Average	2.496	2.451	2.452	2.466	0.721	0.728	0.708	0.719
Ind. CCE									*CCEP*								
20	1.432	1.103	1.024	1.186	0.432	0.351	0.313	0.365	20	1.581	1.313	1.243	1.379	0.475	0.418	0.378	0.424
50	1.387	1.106	1.032	1.175	0.414	0.330	0.294	0.346	50	1.549	1.327	1.261	1.379	0.460	0.396	0.359	0.405
100	1.402	1.065	1.027	1.165	0.397	0.312	0.305	0.338	100	1.559	1.297	1.261	1.373	0.440	0.379	0.374	0.398
Average	1.407	1.091	1.028	1.175	0.414	0.331	0.304	0.350	Average	1.563	1.313	1.255	1.377	0.458	0.398	0.370	0.409
Ind. CCEX									*CCEPX*								
20	1.439	1.104	1.024	1.189	0.434	0.352	0.313	0.366	20	1.581	1.313	1.243	1.379	0.475	0.418	0.378	0.424
50	1.390	1.107	1.032	1.176	0.415	0.331	0.294	0.346	50	1.549	1.327	1.261	1.379	0.460	0.396	0.359	0.405
100	1.404	1.066	1.027	1.166	0.398	0.312	0.305	0.338	100	1.559	1.297	1.261	1.373	0.440	0.379	0.374	0.398
Average	1.411	1.092	1.028	1.177	0.416	0.332	0.304	0.350	Average	1.563	1.313	1.255	1.377	0.458	0.398	0.370	0.409
Ind. IPC									*IPCP*								
20	1.444	1.101	1.021	1.189	0.435	0.351	0.312	0.366	20	1.585	1.316	1.245	1.382	0.476	0.419	0.379	0.424
50	1.368	1.101	1.029	1.166	0.408	0.329	0.293	0.343	50	1.551	1.328	1.262	1.380	0.460	0.396	0.359	0.405
100	1.373	1.059	1.024	1.152	0.389	0.310	0.304	0.334	100	1.560	1.298	1.262	1.373	0.440	0.379	0.374	0.398
Average	1.395	1.087	1.025	1.169	0.411	0.330	0.303	0.348	Average	1.565	1.314	1.256	1.379	0.458	0.398	0.370	0.409
Ind. PCX									*PCPX*								
20	1.578	1.162	1.047	1.262	0.474	0.370	0.320	0.388	20	1.585	1.315	1.243	1.381	0.476	0.419	0.378	0.424
50	1.523	1.159	1.056	1.246	0.453	0.346	0.300	0.366	50	1.551	1.328	1.261	1.380	0.460	0.396	0.359	0.405
100	1.542	1.120	1.052	1.238	0.436	0.328	0.312	0.358	100	1.560	1.298	1.261	1.373	0.440	0.380	0.374	0.398
Average	1.547	1.147	1.052	1.249	0.454	0.348	0.311	0.371	Average	1.565	1.313	1.255	1.378	0.459	0.398	0.370	0.409
Ind. PCX2S									*PCPX2S*								
20	1.482	1.109	1.023	1.205	0.446	0.354	0.313	0.371	20	1.583	1.313	1.242	1.379	0.475	0.418	0.378	0.424
50	1.416	1.109	1.032	1.186	0.423	0.331	0.294	0.349	50	1.550	1.327	1.261	1.379	0.460	0.396	0.359	0.405
100	1.428	1.068	1.027	1.175	0.405	0.313	0.305	0.341	100	1.560	1.297	1.261	1.373	0.440	0.379	0.374	0.398
Average	1.442	1.095	1.027	1.188	0.425	0.333	0.304	0.354	Average	1.564	1.312	1.255	1.377	0.458	0.398	0.370	0.409

Table A76: Forecasting Accuracy Measures, High Heterogeneity – DGP4, Case f: Low Spatial Dependence & High Factor Dependence - SMA Errors

Heterogeneous

N \ T	RMSE 20	RMSE 50	RMSE 100	RMSE Average	Theil's U 20	Theil's U 50	Theil's U 100	Theil's U Average
Ind. OLS								
20	3.181	2.881	2.790	2.950	0.753	0.708	0.660	0.707
50	3.153	2.895	2.804	2.951	0.744	0.681	0.634	0.686
100	3.162	2.865	2.773	2.933	0.719	0.667	0.646	0.677
Average	3.165	2.880	2.789	2.945	0.739	0.685	0.647	0.690
Ind. GLS								
20	3.103	2.864	2.786	2.917	0.733	0.703	0.659	0.698
50	3.066	2.877	2.800	2.914	0.721	0.677	0.633	0.677
100	3.069	2.848	2.767	2.895	0.696	0.662	0.644	0.667
Average	3.079	2.863	2.784	2.909	0.717	0.681	0.645	0.681
Ind. CCE								
20	1.798	1.254	1.123	1.392	0.430	0.315	0.275	0.340
50	1.726	1.209	1.083	1.339	0.411	0.292	0.252	0.318
100	1.733	1.151	1.060	1.315	0.398	0.275	0.255	0.309
Average	1.752	1.205	1.089	1.349	0.413	0.294	0.261	0.322
Ind. CCEX								
20	1.812	1.260	1.125	1.399	0.434	0.316	0.276	0.342
50	1.734	1.212	1.084	1.343	0.413	0.292	0.252	0.319
100	1.738	1.153	1.061	1.317	0.399	0.275	0.255	0.310
Average	1.761	1.208	1.090	1.353	0.415	0.295	0.261	0.324
Ind. IPC								
20	1.806	1.248	1.116	1.390	0.432	0.313	0.274	0.340
50	1.707	1.202	1.078	1.329	0.406	0.290	0.251	0.316
100	1.707	1.144	1.057	1.303	0.392	0.273	0.254	0.306
Average	1.740	1.198	1.084	1.341	0.410	0.292	0.260	0.320
Ind. PCX								
20	2.188	1.434	1.200	1.607	0.523	0.359	0.293	0.392
50	2.112	1.373	1.164	1.550	0.502	0.330	0.270	0.368
100	2.132	1.321	1.144	1.532	0.488	0.314	0.274	0.359
Average	2.144	1.376	1.169	1.563	0.504	0.334	0.279	0.373
Ind. PCX2S								
20	1.859	1.266	1.121	1.415	0.445	0.318	0.275	0.346
50	1.761	1.213	1.082	1.352	0.419	0.293	0.252	0.321
100	1.765	1.155	1.061	1.327	0.405	0.275	0.255	0.312
Average	1.795	1.211	1.088	1.365	0.423	0.295	0.261	0.326

Homogeneous

	RMSE 20	RMSE 50	RMSE 100	RMSE Average	Theil's U 20	Theil's U 50	Theil's U 100	Theil's U Average
*FE**								
20	3.378	3.201	3.147	3.242	0.797	0.784	0.742	0.774
50	3.351	3.221	3.173	3.248	0.786	0.756	0.715	0.752
100	3.374	3.195	3.136	3.235	0.763	0.741	0.728	0.744
Average	3.368	3.206	3.152	3.242	0.782	0.760	0.728	0.757
2WFE								
20	3.989	3.910	3.956	3.952	0.941	0.962	0.939	0.947
50	3.959	3.982	3.981	3.974	0.929	0.936	0.904	0.923
100	4.000	3.960	3.931	3.964	0.903	0.920	0.914	0.912
Average	3.983	3.951	3.956	3.963	0.924	0.939	0.919	0.928
CCEP								
20	1.917	1.440	1.324	1.560	0.457	0.361	0.324	0.381
50	1.860	1.414	1.302	1.525	0.441	0.341	0.303	0.361
100	1.865	1.369	1.288	1.507	0.426	0.326	0.309	0.354
Average	1.881	1.408	1.305	1.531	0.441	0.343	0.312	0.365
CCEPX								
20	1.917	1.440	1.324	1.560	0.457	0.361	0.324	0.381
50	1.860	1.414	1.302	1.525	0.441	0.341	0.303	0.361
100	1.865	1.369	1.288	1.507	0.426	0.326	0.309	0.354
Average	1.881	1.408	1.305	1.531	0.441	0.343	0.312	0.365
IPCP								
20	1.921	1.443	1.326	1.563	0.458	0.362	0.324	0.381
50	1.861	1.415	1.303	1.526	0.441	0.341	0.303	0.362
100	1.865	1.370	1.289	1.508	0.426	0.326	0.309	0.354
Average	1.882	1.409	1.306	1.532	0.442	0.343	0.312	0.366
PCPX								
20	1.930	1.446	1.325	1.567	0.461	0.363	0.324	0.383
50	1.866	1.416	1.303	1.528	0.442	0.341	0.303	0.362
100	1.868	1.370	1.289	1.509	0.427	0.326	0.309	0.354
Average	1.888	1.411	1.306	1.535	0.443	0.344	0.312	0.366
PCPX2S								
20	1.918	1.440	1.323	1.560	0.458	0.361	0.324	0.381
50	1.861	1.414	1.302	1.525	0.441	0.341	0.303	0.361
100	1.865	1.369	1.288	1.507	0.426	0.326	0.309	0.354
Average	1.881	1.408	1.304	1.531	0.441	0.343	0.312	0.365

Table A77: Forecasting Accuracy Measures, High Heterogeneity – DGP4, Case g: High Spatial Dependence & Low Factor Dependence - SMA Errors

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	1.990	1.780	1.730	1.834	0.587	0.556	0.514	0.552	20	2.252	2.122	2.092	2.155	0.662	0.660	0.617	0.646
50	1.953	1.804	1.748	1.835	0.572	0.527	0.486	0.528	50	2.227	2.152	2.114	2.164	0.648	0.626	0.586	0.620
100	1.959	1.768	1.733	1.820	0.545	0.507	0.501	0.518	100	2.242	2.122	2.100	2.155	0.621	0.605	0.605	0.611
Average	1.968	1.784	1.737	1.829	0.568	0.530	0.500	0.533	Average	2.240	2.132	2.102	2.158	0.644	0.631	0.603	0.626
Ind. GLS									*2WFE*								
20	1.951	1.773	1.729	1.818	0.575	0.553	0.513	0.547	20	2.573	2.468	2.491	2.511	0.753	0.764	0.733	0.750
50	1.911	1.796	1.746	1.818	0.559	0.524	0.486	0.523	50	2.519	2.526	2.516	2.520	0.730	0.731	0.697	0.719
100	1.913	1.761	1.731	1.802	0.532	0.504	0.501	0.512	100	2.538	2.493	2.490	2.507	0.699	0.707	0.714	0.707
Average	1.925	1.777	1.735	1.812	0.555	0.527	0.500	0.527	Average	2.543	2.496	2.499	2.513	0.727	0.734	0.715	0.725
Ind. CCE									*CCEP*								
20	1.536	1.191	1.116	1.281	0.458	0.376	0.337	0.390	20	1.666	1.387	1.321	1.458	0.494	0.438	0.398	0.443
50	1.482	1.196	1.123	1.267	0.438	0.354	0.316	0.369	50	1.622	1.402	1.336	1.453	0.477	0.414	0.376	0.422
100	1.494	1.148	1.114	1.252	0.420	0.333	0.327	0.360	100	1.628	1.364	1.333	1.441	0.455	0.395	0.391	0.414
Average	1.504	1.178	1.118	1.267	0.438	0.354	0.327	0.373	Average	1.638	1.384	1.330	1.451	0.475	0.416	0.388	0.426
Ind. CCEX									*CCEPX*								
20	1.550	1.194	1.117	1.287	0.462	0.377	0.338	0.392	20	1.666	1.387	1.321	1.458	0.494	0.438	0.398	0.443
50	1.489	1.198	1.123	1.270	0.440	0.354	0.316	0.370	50	1.622	1.402	1.336	1.453	0.477	0.414	0.376	0.422
100	1.498	1.148	1.114	1.254	0.421	0.334	0.327	0.360	100	1.628	1.364	1.333	1.441	0.455	0.395	0.391	0.414
Average	1.512	1.180	1.118	1.270	0.441	0.355	0.327	0.374	Average	1.638	1.384	1.330	1.451	0.475	0.416	0.388	0.426
Ind. IPC									*IPCP*								
20	1.526	1.189	1.116	1.277	0.454	0.375	0.337	0.389	20	1.670	1.390	1.323	1.461	0.495	0.438	0.398	0.444
50	1.456	1.192	1.121	1.256	0.430	0.352	0.316	0.366	50	1.623	1.403	1.337	1.454	0.477	0.414	0.376	0.422
100	1.460	1.141	1.111	1.237	0.410	0.331	0.326	0.356	100	1.629	1.364	1.333	1.442	0.455	0.395	0.391	0.414
Average	1.481	1.174	1.116	1.257	0.431	0.353	0.326	0.370	Average	1.641	1.386	1.331	1.452	0.476	0.416	0.388	0.427
Ind. PCX									*PCPX*								
20	1.681	1.249	1.138	1.356	0.499	0.394	0.344	0.412	20	1.670	1.389	1.321	1.460	0.496	0.438	0.398	0.444
50	1.612	1.247	1.146	1.335	0.475	0.368	0.323	0.389	50	1.624	1.402	1.336	1.454	0.477	0.414	0.376	0.423
100	1.627	1.199	1.137	1.321	0.456	0.348	0.334	0.379	100	1.629	1.364	1.333	1.442	0.455	0.396	0.391	0.414
Average	1.640	1.231	1.140	1.337	0.477	0.370	0.333	0.393	Average	1.641	1.385	1.330	1.452	0.476	0.416	0.388	0.427
Ind. PCX2S									*PCPX2S*								
20	1.583	1.197	1.115	1.298	0.471	0.378	0.337	0.395	20	1.667	1.387	1.320	1.458	0.495	0.437	0.398	0.443
50	1.511	1.200	1.123	1.278	0.446	0.354	0.316	0.372	50	1.622	1.402	1.336	1.453	0.477	0.414	0.376	0.422
100	1.521	1.150	1.115	1.262	0.427	0.334	0.327	0.363	100	1.628	1.364	1.333	1.441	0.455	0.395	0.391	0.414
Average	1.539	1.182	1.117	1.279	0.448	0.355	0.327	0.377	Average	1.639	1.384	1.329	1.451	0.475	0.416	0.388	0.426

Table A78: Forecasting Accuracy Measures, High Heterogeneity – DGP4, Case h: High Spatial Dependence & High Factor Dependence - SMA Errors

	Heterogeneous									*Homogeneous*							
T	RMSE				Theil's U					RMSE				Theil's U			
N	20	50	100	Average	20	50	100	Average		20	50	100	Average	20	50	100	Average
Ind. OLS									*FE**								
20	3.225	2.915	2.826	2.989	0.759	0.712	0.665	0.712	20	3.413	3.230	3.179	3.274	0.800	0.786	0.745	0.777
50	3.191	2.931	2.839	2.987	0.748	0.686	0.639	0.691	50	3.382	3.251	3.204	3.279	0.789	0.758	0.718	0.755
100	3.197	2.896	2.806	2.967	0.723	0.671	0.650	0.681	100	3.403	3.222	3.165	3.263	0.765	0.743	0.730	0.746
Average	3.204	2.914	2.824	2.981	0.743	0.690	0.652	0.695	Average	3.400	3.234	3.182	3.272	0.785	0.763	0.731	0.759
Ind. GLS									*2WFE*								
20	3.144	2.897	2.822	2.955	0.738	0.707	0.664	0.703	20	4.027	3.942	3.990	3.986	0.944	0.964	0.942	0.950
50	3.103	2.913	2.835	2.950	0.726	0.681	0.638	0.682	50	3.987	4.009	4.011	4.002	0.930	0.937	0.906	0.925
100	3.103	2.879	2.801	2.927	0.700	0.666	0.648	0.671	100	4.026	3.984	3.956	3.989	0.904	0.921	0.915	0.914
Average	3.116	2.896	2.819	2.944	0.721	0.685	0.650	0.685	Average	4.013	3.978	3.986	3.992	0.926	0.941	0.921	0.929
Ind. CCE									*CCEP*								
20	1.884	1.333	1.208	1.475	0.448	0.333	0.294	0.359	20	1.989	1.508	1.397	1.631	0.472	0.376	0.340	0.396
50	1.807	1.293	1.170	1.423	0.428	0.310	0.271	0.336	50	1.923	1.484	1.375	1.594	0.453	0.356	0.318	0.376
100	1.811	1.228	1.145	1.395	0.414	0.292	0.274	0.326	100	1.925	1.432	1.358	1.572	0.438	0.340	0.324	0.367
Average	1.834	1.284	1.174	1.431	0.430	0.312	0.280	0.340	Average	1.946	1.475	1.377	1.599	0.454	0.357	0.327	0.379
Ind. CCEX									*CCEPX*								
20	1.904	1.340	1.210	1.485	0.453	0.335	0.295	0.361	20	1.989	1.508	1.397	1.631	0.472	0.376	0.340	0.396
50	1.817	1.296	1.171	1.428	0.430	0.311	0.271	0.337	50	1.923	1.484	1.375	1.594	0.453	0.356	0.318	0.376
100	1.817	1.230	1.146	1.397	0.415	0.292	0.274	0.327	100	1.925	1.432	1.358	1.572	0.437	0.340	0.324	0.367
Average	1.846	1.289	1.176	1.437	0.433	0.313	0.280	0.342	Average	1.946	1.475	1.377	1.599	0.454	0.357	0.327	0.379
Ind. IPC									*IPCP*								
20	1.882	1.328	1.202	1.470	0.447	0.332	0.293	0.357	20	1.992	1.510	1.400	1.634	0.472	0.377	0.340	0.397
50	1.785	1.286	1.166	1.412	0.423	0.308	0.270	0.334	50	1.924	1.485	1.376	1.595	0.453	0.356	0.318	0.376
100	1.782	1.221	1.141	1.382	0.407	0.290	0.273	0.323	100	1.925	1.433	1.359	1.572	0.438	0.340	0.324	0.367
Average	1.816	1.278	1.170	1.421	0.426	0.310	0.279	0.338	Average	1.947	1.476	1.378	1.600	0.454	0.357	0.327	0.380
Ind. PCX									*PCPX*								
20	2.266	1.506	1.281	1.684	0.538	0.375	0.312	0.408	20	2.002	1.514	1.399	1.638	0.475	0.378	0.340	0.398
50	2.180	1.450	1.246	1.625	0.516	0.347	0.288	0.383	50	1.929	1.486	1.376	1.597	0.455	0.356	0.318	0.376
100	2.197	1.390	1.223	1.603	0.501	0.329	0.292	0.374	100	1.927	1.433	1.358	1.573	0.438	0.340	0.324	0.367
Average	2.214	1.449	1.250	1.638	0.518	0.350	0.297	0.388	Average	1.953	1.478	1.378	1.603	0.456	0.358	0.327	0.380
Ind. PCX2S									*PCPX2S*								
20	1.944	1.344	1.206	1.498	0.462	0.336	0.294	0.364	20	1.990	1.508	1.396	1.631	0.472	0.376	0.340	0.396
50	1.842	1.297	1.170	1.436	0.436	0.311	0.271	0.339	50	1.924	1.484	1.375	1.594	0.453	0.356	0.318	0.376
100	1.844	1.232	1.145	1.407	0.421	0.292	0.274	0.329	100	1.925	1.432	1.358	1.572	0.438	0.340	0.324	0.367
Average	1.877	1.291	1.174	1.447	0.440	0.313	0.279	0.344	Average	1.946	1.475	1.376	1.599	0.454	0.357	0.327	0.379

Appendix B

Additional Results for Chapter 2

Table B1: Size – DGP 1: No Factor Dependence, No Spatial Dependence

			Overall EPA Test												Joint EPA Test									
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	0.75	0.90	0.55	0.80	1.35	4.75	4.20	3.65	5.70	5.50	$J_{n,T}^{(1)}$	10	5.65	2.80	1.80	1.60	0.90	16.90	8.60	8.20	7.40	4.55
		20	1.10	0.95	1.15	1.10	1.15	5.55	4.55	5.95	4.70	5.55		20	11.15	3.30	2.90	1.05	1.40	26.80	12.70	10.45	7.05	5.85
		30	0.85	1.20	1.10	1.30	0.85	4.80	5.00	5.05	5.25	4.75		30	15.20	4.15	2.85	1.90	1.15	33.65	15.50	9.95	8.05	5.15
		50	1.15	1.00	1.45	1.20	1.00	4.75	5.00	5.90	5.85	5.05		50	22.25	6.05	3.85	2.25	1.10	45.35	18.05	13.70	9.55	6.15
		100	0.95	1.00	1.05	1.05	1.00	4.40	5.45	4.80	4.85	4.90		100	40.40	10.55	5.45	2.85	2.05	66.90	27.70	17.55	10.15	7.95
		200	0.85	0.85	1.15	0.80	1.10	5.55	4.80	5.55	4.70	5.50		200	74.35	19.90	9.00	4.10	2.35	89.95	43.00	25.30	14.35	9.30
Truncated	$S_{n,T}^{(2)}$	10	1.65	1.05	0.65	1.10	1.35	6.55	5.25	4.20	5.80	5.50	$J_{n,T}^{(2)}$	10	29.80	9.20	5.75	3.05	1.20	43.25	20.50	14.50	10.60	5.65
		20	2.30	1.20	1.25	1.10	1.15	7.40	5.75	6.75	4.95	5.50		20	35.65	43.65	35.20	10.15	3.50	40.45	52.55	49.70	23.95	12.00
		30	1.80	1.40	1.15	1.45	0.80	5.75	6.00	5.25	5.50	4.95		30	37.00	46.45	49.40	18.25	4.05	41.45	53.95	62.65	34.70	13.20
		50	1.65	1.30	1.50	1.25	0.95	5.50	4.55	5.90	6.05	5.15		50	35.60	49.15	60.50	28.35	6.55	38.95	54.20	69.10	47.75	19.05
		100	1.10	1.00	1.10	1.05	1.00	5.20	5.95	5.30	4.90	5.00		100	39.50	56.25	79.05	56.75	13.95	40.85	58.75	81.35	75.50	31.20
		200	1.20	1.05	1.10	0.75	1.10	6.15	5.05	5.55	4.95	5.55		200	33.30	41.55	51.05	79.20	65.55	34.45	42.65	53.30	81.10	82.35
Bartlett	$S_{n,T}^{(2)}$	10	0.75	0.90	0.55	0.80	1.35	4.75	4.20	3.65	5.70	5.50	$J_{n,T}^{(2)}$	10	5.65	2.80	1.80	1.60	0.90	16.90	8.60	8.20	7.40	4.55
		20	1.30	0.95	1.25	1.10	1.15	5.90	4.75	5.85	4.60	5.70		20	20.85	5.75	3.95	1.60	1.60	40.95	18.35	12.30	8.10	6.85
		30	0.95	1.40	1.05	1.35	0.75	5.20	5.00	5.10	5.35	4.80		30	30.30	7.65	4.15	2.50	1.25	51.00	22.05	13.60	9.50	5.95
		50	1.15	1.10	1.35	1.15	1.00	4.95	4.95	6.05	5.90	5.10		50	46.95	11.75	6.85	3.00	1.50	68.15	29.10	18.55	11.80	7.15
		100	1.10	0.90	1.00	1.05	1.00	4.65	5.65	5.10	4.95	4.90		100	92.25	37.35	16.85	6.70	2.80	97.40	60.25	36.45	18.95	10.80
		200	1.00	1.05	1.10	0.80	1.05	5.60	4.85	5.50	4.60	5.55		200	100.00	77.10	39.95	14.80	4.95	100.00	91.15	65.15	33.90	16.30
Parzen	$S_{n,T}^{(2)}$	10	0.75	0.90	0.55	0.80	1.35	4.75	4.20	3.65	5.70	5.50	$J_{n,T}^{(2)}$	10	5.65	2.80	1.80	1.60	0.90	16.90	8.60	8.20	7.40	4.55
		20	1.20	0.95	1.15	1.10	1.10	5.60	4.65	5.75	4.65	5.65		20	12.95	3.50	3.15	1.10	1.50	29.70	13.85	11.05	7.00	6.10
		30	0.80	1.20	1.10	1.30	0.80	4.90	5.00	5.10	5.25	4.80		30	17.35	4.60	3.30	2.10	1.10	37.55	16.25	10.35	8.10	5.40
		50	1.15	1.10	1.30	1.25	1.00	4.85	4.80	5.95	5.85	5.05		50	25.65	6.90	4.15	2.30	1.20	49.95	20.20	14.25	9.80	6.50
		100	1.10	1.00	1.00	1.05	1.00	4.50	5.55	5.00	4.85	4.95		100	74.50	21.50	10.10	4.60	2.20	89.35	43.70	26.75	14.15	9.00
		200	0.85	0.95	1.15	0.80	1.05	5.45	4.90	5.55	4.60	5.60		200	97.80	47.00	19.65	8.40	3.15	99.70	71.10	42.70	23.10	12.45
Tukey	$S_{n,T}^{(2)}$	10	0.75	0.90	0.55	0.80	1.35	4.75	4.20	3.65	5.70	5.50	$J_{n,T}^{(2)}$	10	5.65	2.80	1.80	1.60	0.90	16.90	8.60	8.20	7.40	4.55
		20	1.30	1.00	1.25	1.05	1.15	5.95	4.80	5.85	4.60	5.60		20	20.00	5.45	3.95	1.55	1.55	39.65	17.80	12.00	7.95	6.70
		30	0.95	1.40	1.05	1.35	0.80	5.15	4.95	5.05	5.35	4.80		30	28.20	6.85	4.05	2.35	1.25	49.70	21.30	13.30	9.45	5.95
		50	1.15	1.10	1.30	1.20	1.00	4.90	4.90	6.10	5.85	5.00		50	44.25	11.15	6.30	2.90	1.40	65.20	27.45	18.10	11.25	6.90
		100	1.10	0.90	1.00	1.05	1.00	4.65	5.70	5.15	4.90	4.90		100	95.75	41.50	19.05	7.20	2.90	98.70	64.85	38.85	20.20	11.00
		200	0.95	1.05	1.15	0.80	1.05	5.60	4.80	5.60	4.60	5.60		200	100.00	80.70	43.05	16.00	5.00	100.00	92.85	67.75	35.30	16.85
QS	$S_{n,T}^{(2)}$	10	0.90	0.90	0.60	0.90	1.30	4.75	4.25	3.70	5.65	5.65	$J_{n,T}^{(2)}$	10	5.95	2.80	1.80	1.55	0.95	16.85	8.85	8.05	7.35	4.60
		20	1.40	1.15	1.25	1.10	1.15	6.25	5.05	5.95	4.65	5.35		20	36.75	9.85	5.50	2.25	1.90	57.80	23.50	15.50	9.55	7.30
		30	1.05	1.40	1.05	1.40	0.75	5.25	5.10	5.20	5.45	4.85		30	52.50	13.25	6.60	3.30	1.65	71.55	30.50	17.50	11.85	6.75
		50	1.20	1.20	1.40	1.20	1.00	4.95	4.75	6.05	5.95	5.05		50	75.95	21.65	10.10	4.90	2.05	88.15	42.40	26.20	14.90	8.40
		100	1.10	0.95	1.05	1.05	1.00	4.90	5.65	5.20	4.95	4.90		100	99.95	67.60	33.70	11.70	4.05	99.95	84.25	56.50	28.55	13.55
		200	1.10	1.05	1.10	0.80	1.05	5.60	4.95	5.60	4.70	5.50		200	100.00	99.00	78.85	34.20	9.20	100.00	99.80	91.00	57.55	26.55
	$S_{n,T}^{(3)}$	10	2.90	1.60	1.20	1.15	1.30	9.35	6.15	5.20	6.15	6.10	$J_{n,T}^{(3)}$	10		39.00	19.80	7.95	2.40		54.70	35.30	20.80	9.15
		20	4.05	2.00	1.85	1.35	1.20	10.00	6.70	7.35	5.25	5.85		20			81.85	36.10	10.30			89.75	54.00	23.05
		30	3.20	2.45	1.30	1.30	0.95	9.00	7.85	6.20	6.00	4.70		30				85.90	26.45				93.40	45.95
		50	3.25	2.30	2.00	1.55	1.10	9.15	7.55	6.70	6.60	5.45		50					82.30					91.50
		100	3.60	2.45	1.50	1.50	1.20	8.30	7.45	7.10	5.90	5.35		100										
		200	4.20	2.05	1.65	0.95	1.30	10.30	7.45	6.75	5.80	5.85		200										
Fixed	$S_{n,T}^{(4)}$	10	0.45	1.15	0.55	1.05	1.00	5.05	4.75	4.65	5.85	5.60	$J_{n,T}^{(4)}$	10	0.75	0.85	1.10	2.05	1.60	4.60	5.40	7.80	9.25	7.10
		20	0.80	0.80	1.00	1.05	1.15	5.50	4.55	5.80	4.55	5.00		20	0.90	0.70	0.80	0.95	1.55	6.15	5.50	5.70	6.40	7.35
		30	0.75	1.20	0.70	1.40	1.00	4.80	4.65	4.70	5.20	4.75		30	0.95	0.85	0.90	1.40	1.05	6.05	5.35	4.85	5.55	6.45
		50	0.75	1.05	1.35	1.05	1.00	4.35	4.95	5.20	5.55	5.15		50	1.35	0.95	0.85	0.60	1.15	7.10	5.50	5.20	5.55	5.65
		100	0.80	1.10	0.85	1.05	0.95	4.40	5.45	5.15	5.05	4.70		100	4.05	1.50	1.20	0.95	0.85	13.35	7.15	6.20	4.85	5.85
		200	0.85	0.85	1.00	0.65	1.15	5.35	4.75	5.25	4.70	5.45		200	10.15	2.15	1.30	0.95	1.15	21.80	9.95	5.55	5.35	5.15
Expanding	$S_{n,T}^{(4)}$	10	0.50	1.05	0.65	0.90	1.30	4.95	4.60	4.10	5.75	5.25	$J_{n,T}^{(4)}$	10	0.20	0.75	0.95	1.40	1.05	2.85	4.05	5.05	6.20	5.80
		20	0.80	0.80	1.00	1.05	1.15	5.50	4.55	5.80	4.55	5.00		20	0.90	0.70	0.80	0.95	1.55	6.15	5.50	5.70	6.40	7.35
		30	0.75	1.20	0.70	1.40	1.00	4.80	4.65	4.70	5.20	4.75		30	0.95	0.85	0.90	1.40	1.05	6.05	5.35	4.85	5.55	6.45
		50	0.75	1.05	1.35	1.05	1.00	4.35	4.95	5.20	5.55	5.15		50	1.35	0.95	0.85	0.60	1.15	7.10	5.50	5.20	5.55	5.65
		100	0.70	1.15	0.90	1.00	1.00	4.65	5.35	4.80	5.35	4.85		100	9.10	1.95	1.00	1.00	1.30	19.20	9.05	7.10	6.00	6.55
		200	0.80	0.90	1.00	0.65	1.30	4.85	4.65	5.20	4.60	5.55		200	18.45	4.75	1.50	1.10	1.10	28.90	12.80	8.30	6.60	5.45
Fixed	$S_{n,T}^{(5)}$	10	0.40	1.00	0.60	1.05	1.00	4.50	4.35	4.40	5.90	5.95	$J_{n,T}^{(5)}$	10	3.95	0.60	0.50	1.20	1.60	7.65	4.70	6.35	7.65	6.65
		20	0.60	0.55	0.90	0.80	1.20	5.00	4.60	5.75	4.50	5.30		20	5.05	9.55	3.05	0.70	1.25	7.90	15.65	8.20	4.70	6.25
		30	0.45	0.80	0.85	1.30	0.90	4.30	4.80	4.50	5.30	4.85		30	6.50	11.90	6.80	1.20	1.05	8.90	17.45	12.90	5.80	5.65
		50	0.50	1.00	1.25	1.00	0.85	4.25	4.65	5.45	5.65	5.25		50	6.20	13.35	12.45	1.25	1.05	7.50	18.65	21.45	6.15	5.20
		100	0.65	1.05	0.80	1.05	0.90	4.75	5.70	5.15	5.15	4.75		100	8.30	18.05	21.35	1.55	0.65	9.35	23.30	32.25	6.50	4.55
		200	0.80	0.90	1.05	0.75	1.10	5.65	4.85	5.05	4.95	5.40		200	4.50	11.20	19.65	33.20	0.80	5.00	13.60	23.10	43.60	6.00
Expanding	$S_{n,T}^{(5)}$	10	0.50	0.95	0.40	1.05	1.30	4.30	4.55	4.05	5.65	5.50	$J_{n,T}^{(5)}$	10	4.35	0.50	0.40	1.05	1.15	8.10	3.40	4.65	5.70	5.50
		20	0.60	0.55	0.90	0.80	1.20	5.00	4.60	5.75	4.50	5.30		20	5.05	9.55	3.05	0.70	1.25	7.90	15.65	8.20	4.70	6.25
		30	0.45	0.80	0.85	1.30	0.90	4.30	4.80	4.50	5.30	4.85		30	6.50	11.90	6.80	1.20	1.05	8.90	17.45	12.90	5.80	5.65
		50	0.50	1.00	1.25	1.00	0.85	4.25	4.65	5.45	5.65	5.25		50	6.20	13.35	12.45	1.25	1.05	7.50	18.65	21.45	6.15	5.20
		100	0.65	1.05	1.00	1.05	0.95	4.65	5.70	4.70	4.95	4.75		100	6.05	18.90	21.30	1.40	1.00	7.30	23.05	32.15	6.65	5.25
		200	0.70	0.80	1.00	0.70	1.20	4.70	4.65	4.80	5.05	5.55		200	3.35	12.20	19.65	35.85	1.05	3.65	13.85	23.00	47.10	6.45

Table B2: Size – DGP 1: No Factor Dependence, High Spatial Dependence

			Overall EPA Test												Joint EPA Test									
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S^{(1)}_{n,T}$	10	38.25	35.70	34.90	32.80	33.40	51.80	47.50	47.15	46.70	46.00	$J^{(1)}_{n,T}$	10	15.60	12.55	11.25	10.75	10.80	23.00	19.85	17.90	16.25	16.25
		20	40.40	40.65	40.50	39.55	40.50	52.85	52.65	53.35	52.90	52.10		20	19.30	15.10	12.40	11.90	11.20	28.90	22.45	20.15	18.65	16.70
		30	40.10	38.75	40.10	39.55	40.20	52.85	51.35	51.65	52.35	52.90		30	22.25	14.15	12.25	12.45	10.55	34.10	22.85	20.35	18.70	16.50
		50	41.10	38.25	39.20	40.30	38.05	52.50	50.80	51.35	52.70	51.50		50	30.70	16.10	14.40	12.70	11.55	42.85	26.75	24.15	20.25	18.25
		100	33.00	34.25	35.30	36.25	36.00	47.15	46.30	48.20	48.45	48.90		100	41.80	23.45	17.60	14.40	13.95	56.80	33.85	27.65	22.75	23.00
		200	39.20	37.35	39.45	39.45	38.00	50.85	50.55	52.10	50.50	50.55		200	65.15	29.60	21.70	17.50	13.65	77.20	45.10	33.35	28.05	22.55
Truncated	$S^{(2)}_{n,T}$	10	9.20	8.75	8.70	8.90	9.05	20.95	20.95	19.70	18.40	18.45	$J^{(2)}_{n,T}$	10	2.20	0.35	0.35	0.05	0.40	4.15	1.40	1.20	0.75	1.20
		20	4.95	4.55	3.85	3.70	4.25	14.50	13.70	13.25	11.95	12.30		20	9.20	5.90	4.70	3.05	2.00	11.35	7.15	5.90	3.90	2.80
		30	3.85	3.95	4.65	4.20	4.65	12.70	12.65	13.65	12.80	13.05		30	11.75	10.05	8.65	7.85	6.70	14.40	12.05	11.00	9.60	8.35
		50	4.75	3.90	4.15	3.95	4.80	13.30	14.45	12.65	12.65	13.15		50	14.90	12.45	10.85	10.20	8.40	17.15	14.80	12.65	12.10	10.00
		100	1.75	1.60	1.45	1.15	1.75	7.45	6.85	6.60	7.10	7.35		100	18.05	18.05	18.10	18.30	20.20	19.85	20.25	20.40	21.05	22.70
		200	1.95	1.55	1.25	1.40	1.85	8.35	6.50	6.20	7.50	7.20		200	19.90	21.75	21.50	25.50	28.20	21.30	23.60	22.90	27.35	31.45
Bartlett	$S^{(2)}_{n,T}$	10	38.25	35.70	34.90	32.80	33.40	51.80	47.50	47.15	46.70	46.00	$J^{(2)}_{n,T}$	10	15.60	12.55	11.25	10.75	10.80	23.00	19.85	17.90	16.25	16.25
		20	18.45	18.80	18.85	17.70	17.80	31.95	31.40	32.05	30.40	30.70		20	3.30	1.60	1.15	0.60	0.65	7.70	3.95	2.70	2.20	1.95
		30	17.50	16.75	18.45	18.40	19.05	31.50	30.30	31.90	30.40	31.55		30	3.70	1.05	0.70	0.35	0.50	9.50	2.80	2.40	1.35	1.10
		50	18.40	18.30	17.60	17.45	17.35	32.30	30.55	30.75	30.85	28.55		50	5.70	0.85	0.25	0.25	0.15	11.40	2.55	0.75	0.90	0.60
		100	7.90	7.05	7.10	7.45	7.75	16.45	18.00	17.15	19.20	18.40		100	1.75	0.00	0.00	0.00	0.00	4.25	0.00	0.00	0.00	0.00
		200	9.95	8.55	8.35	9.55	8.95	21.45	20.25	20.40	19.95	20.30		200	21.35	0.10	0.00	0.00	0.00	37.70	0.30	0.00	0.00	0.00
Parzen	$S^{(2)}_{n,T}$	10	38.25	35.70	34.90	32.80	33.40	51.80	47.50	47.15	46.70	46.00	$J^{(2)}_{n,T}$	10	15.60	12.55	11.25	10.75	10.80	23.00	19.85	17.90	16.25	16.25
		20	29.15	28.55	29.15	27.50	28.05	42.20	41.90	41.75	40.90	41.90		20	7.05	5.00	3.80	3.30	3.10	13.80	8.90	6.80	6.00	6.10
		30	28.20	27.00	29.25	28.05	29.55	42.25	40.70	41.65	41.00	41.70		30	7.75	3.50	3.25	2.65	2.25	14.05	7.55	5.95	6.00	4.45
		50	29.40	27.70	28.00	28.05	25.45	42.65	39.90	41.15	42.50	39.40		50	8.90	3.65	2.00	1.65	1.55	16.80	6.85	5.35	4.25	3.55
		100	11.95	12.15	12.15	13.40	13.15	22.90	23.85	25.15	25.45	25.85		100	1.60	0.00	0.00	0.00	0.00	3.95	0.15	0.05	0.00	0.05
		200	17.45	15.60	15.30	15.40	16.10	28.55	27.75	28.85	28.00	27.95		200	7.90	0.15	0.00	0.00	0.00	17.35	0.20	0.00	0.00	0.00
Tukey	$S^{(2)}_{n,T}$	10	38.25	35.70	34.90	32.80	33.40	51.80	47.50	47.15	46.70	46.00	$J^{(2)}_{n,T}$	10	15.60	12.55	11.25	10.75	10.80	23.00	19.85	17.90	16.25	16.25
		20	19.70	19.85	20.00	19.10	18.80	32.90	32.40	33.15	31.80	32.25		20	5.00	1.95	1.50	0.75	0.85	9.80	4.95	3.10	2.40	2.35
		30	18.35	18.05	19.55	19.75	20.50	33.05	31.85	33.00	31.35	32.95		30	5.15	1.55	0.90	0.55	0.55	11.35	3.80	2.70	1.90	1.50
		50	19.90	19.80	18.75	18.85	18.65	33.50	31.40	32.00	32.35	29.75		50	6.70	1.20	0.50	0.35	0.20	13.40	3.35	1.35	1.05	0.75
		100	7.55	6.70	6.90	7.30	7.55	16.20	17.20	16.75	18.85	18.10		100	20.40	0.30	0.05	0.00	0.00	34.50	1.35	0.20	0.00	0.05
		200	10.20	8.75	8.55	9.55	9.00	21.50	20.35	20.45	20.00	20.40		200	86.60	2.90	0.30	0.05	0.00	93.25	9.20	1.10	0.10	0.00
QS	$S^{(2)}_{n,T}$	10	32.10	29.75	29.55	28.05	29.00	47.85	42.80	43.05	41.55	41.55	$J^{(2)}_{n,T}$	10	10.95	8.00	7.95	6.85	7.20	17.80	14.60	12.60	11.90	12.15
		20	13.85	13.55	13.35	12.25	12.30	25.85	25.50	25.00	24.00	24.30		20	5.95	1.20	1.05	0.20	0.50	12.65	4.35	2.40	2.05	1.55
		30	12.05	12.45	13.50	12.75	13.10	24.80	24.00	25.75	24.50	25.80		30	9.35	1.15	0.35	0.25	0.20	19.20	3.85	2.25	1.00	1.05
		50	12.40	13.75	12.55	12.35	12.85	26.25	24.40	24.20	24.75	23.20		50	17.85	1.35	0.20	0.15	0.15	31.95	4.70	1.20	0.80	0.40
		100	4.60	4.10	4.35	4.25	4.75	12.55	12.60	12.55	13.90	13.70		100	65.10	2.35	0.40	0.00	0.05	81.35	8.10	1.90	0.10	0.15
		200	6.45	4.35	4.35	5.60	5.80	15.95	14.40	14.45	14.45	14.90		200	100.00	49.40	7.70	0.50	0.05	100.00	70.90	20.65	3.45	0.20
	$S^{(3)}_{n,T}$	10	2.50	1.60	1.50	1.25	1.35	8.00	6.80	6.45	5.90	6.25	$J^{(3)}_{n,T}$	10		39.85	18.35	7.25	3.05		56.25	35.30	18.55	10.75
		20	2.25	1.80	1.65	0.90	1.25	9.10	7.30	5.65	5.20	5.60		20			83.15	36.40	10.00			91.55	54.35	22.15
		30	2.45	1.40	1.75	1.45	1.00	7.65	6.45	6.05	5.55	5.30		30				84.30	27.05				92.10	44.85
		50	3.05	1.45	0.90	1.00	1.50	9.80	7.50	5.40	5.80	5.90		50					83.95					92.35
		100	3.20	1.95	1.60	1.25	1.25	9.35	7.10	6.45	6.30	6.05		100										
		200	4.20	2.05	1.35	1.30	1.30	10.40	6.30	5.80	6.20	5.55		200										
Fixed	$S^{(4)}_{n,T}$	10	0.00	0.25	0.45	0.50	1.05	2.85	3.60	4.10	4.95	5.30	$J^{(4)}_{n,T}$	10	2.35	2.90	3.95	4.35	4.25	9.20	10.45	11.40	12.80	12.55
		20	0.10	0.55	0.65	0.45	0.95	2.55	3.85	3.95	4.15	4.95		20	3.60	4.05	5.65	5.40	7.80	9.95	11.35	12.70	12.85	16.30
		30	0.30	0.55	0.75	0.85	0.70	4.00	4.50	4.55	4.50	4.50		30	4.10	6.15	6.45	6.30	8.40	10.60	13.30	13.35	13.50	15.20
		50	0.95	1.00	0.90	0.85	1.15	6.35	6.60	5.20	5.45	5.35		50	5.65	5.25	5.65	7.55	8.70	13.55	12.70	13.50	15.30	15.05
		100	5.20	6.55	7.00	8.20	7.90	13.90	15.85	16.65	17.20	17.80		100	9.70	9.70	9.55	10.80	11.40	18.65	17.00	18.05	18.00	19.60
		200	6.80	8.35	8.45	8.70	10.25	15.00	17.80	17.95	19.50	20.40		200	12.90	9.35	9.10	10.55	10.10	22.35	17.65	16.30	17.70	18.20
Expanding	$S^{(4)}_{n,T}$	10	0.20	0.60	0.60	0.45	0.90	3.50	3.85	4.30	4.40	5.00	$J^{(4)}_{n,T}$	10	4.35	5.75	7.10	6.70	7.80	10.55	12.15	13.10	12.85	14.65
		20	0.10	0.55	0.65	0.45	0.95	2.55	3.85	3.95	4.15	4.95		20	3.60	4.05	5.65	5.40	7.80	9.95	11.35	12.70	12.85	16.30
		30	0.30	0.55	0.75	0.85	0.70	4.00	4.50	4.55	4.50	4.50		30	4.10	6.15	6.45	6.30	8.40	10.60	13.30	13.35	13.50	15.20
		50	0.95	1.00	0.90	0.85	1.15	6.35	6.60	5.20	5.45	5.35		50	5.65	5.25	5.65	7.55	8.70	13.55	12.70	13.50	15.30	15.05
		100	2.25	3.90	3.45	4.40	4.05	8.85	11.25	11.45	12.10	12.05		100	12.75	9.50	10.10	11.05	11.85	21.40	17.45	19.00	19.60	19.10
		200	3.35	4.15	4.35	4.45	5.40	11.10	12.30	12.05	13.10	14.10		200	18.40	11.30	8.50	9.85	9.05	26.30	20.60	17.55	17.55	17.85
Fixed	$S^{(5)}_{n,T}$	10	0.00	0.25	0.45	0.40	1.05	2.80	3.40	4.10	4.80	5.15	$J^{(5)}_{n,T}$	10	6.00	7.20	5.45	3.50	3.50	9.75	15.35	12.90	12.70	11.55
		20	0.00	0.50	0.60	0.40	0.65	2.20	3.45	3.65	3.80	4.45		20	4.40	7.20	7.40	8.15	4.20	5.95	10.05	10.75	11.70	8.05
		30	0.05	0.30	0.40	0.45	0.55	2.45	2.85	3.55	3.65	3.60		30	5.45	8.05	8.40	11.00	9.85	7.00	10.50	11.55	14.50	15.70
		50	0.30	0.30	0.15	0.30	0.55	3.65	3.80	3.25	3.75	3.55		50	5.80	8.85	12.30	13.45	18.35	6.90	10.80	14.90	16.15	23.70
		100	0.35	0.90	1.05	1.25	0.80	4.45	4.75	4.85	5.45	4.95		100	5.00	9.80	12.40	20.05	23.00	6.00	11.40	14.50	22.30	27.35
		200	0.60	0.95	0.80	1.00	1.25	5.45	5.00	4.55	5.00	4.95		200	3.95	10.45	14.80	19.35	26.45	4.35	11.25	16.00	21.75	29.50
Expanding	$S^{(5)}_{n,T}$	10	0.10	0.20	0.35	0.35	0.75	2.60	2.95	3.50	3.80	4.30	$J^{(5)}_{n,T}$	10	2.60	2.20	1.70	1.50	1.25	4.05	3.50	3.30	3.05	2.75
		20	0.00	0.50	0.60	0.40	0.65	2.20	3.45	3.65	3.80	4.45		20	4.40	7.20	7.40	8.15	4.20	5.95	10.05	10.75	11.70	8.05
		30	0.05	0.30	0.40	0.45	0.55	2.45	2.85	3.55	3.65	3.60		30	5.45	8.05	8.40	11.00	9.85	7.00	10.50	11.55	14.50	15.70
		50	0.30	0.30	0.15	0.30	0.55	3.65	3.80	3.25	3.75	3.55		50	5.80	8.85	12.30	13.45	18.35	6.90	10.80	14.90	16.15	23.70
		100	0.50	0.80	0.80	0.85	0.95	4.10	4.85	4.40	4.80	4.25		100	5.25	10.10	14.35	19.70	21.90	5.60	11.50	16.90	23.20	26.10
		200	0.35	0.85	0.80	1.00	1.00	5.45	4.40	4.65	4.10	4.60		200	3.35	9.60	13.80	18.90	29.25	3.85	10.10	15.05	21.45	31.95

Table B3: Size – DGP 2: Factor Dependence, No Spatial Dependence

			Overall EPA Test												Joint EPA Test										
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size					
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	
	$S^{(1)}_{n,T}$	10	34.40	30.75	32.05	30.30	30.65	45.80	43.75	44.90	43.20	43.30	$J^{(1)}_{n,T}$	10	17.35	12.10	11.10	10.20	9.10	24.35	17.15	16.95	15.20	14.75	
		20	48.95	47.20	47.40	46.55	46.70	59.25	57.20	58.40	57.05	57.70		20	22.00	16.70	14.35	14.45	13.45	28.50	21.45	20.45	19.10	18.20	
		30	56.30	55.70	54.75	53.05	54.00	66.35	65.70	64.20	63.65	62.85		30	23.10	19.30	17.00	16.35	14.05	29.40	24.10	20.75	20.90	18.35	
		50	63.60	64.50	62.55	63.80	64.20	71.80	72.35	71.40	71.95	72.65		50	28.20	22.20	18.85	18.85	18.70	33.20	26.15	22.40	22.50	23.30	
		100	75.50	72.90	74.05	74.70	74.90	82.00	78.45	80.85	79.80	80.20		100	33.30	25.15	23.90	22.45	21.05	36.25	28.00	27.00	26.50	24.70	
		200	81.45	81.35	82.05	81.00	81.05	85.85	85.65	86.45	85.75	85.60		200	37.40	30.10	28.50	24.80	25.45	40.40	32.75	30.75	27.30	27.80	
Truncated	$S^{(2)}_{n,T}$	10	14.90	12.45	12.30	11.80	11.30	27.30	23.05	22.95	22.45	22.30	$J^{(2)}_{n,T}$	10	9.95	6.55	5.55	4.20	3.85	14.70	9.25	7.80	6.20	5.40	
		20	13.30	11.15	9.35	9.80	9.60	24.00	21.45	21.00	19.45	19.45		20	14.85	12.10	9.00	8.95	7.90	18.05	14.85	11.15	11.30	10.10	
		30	17.00	16.80	14.30	14.95	13.25	29.05	28.50	27.15	27.15	25.20		30	14.30	12.25	10.00	10.35	10.65	16.70	14.75	11.90	12.00	12.35	
		50	28.40	26.05	23.05	23.80	24.85	40.85	40.40	36.40	37.25	37.45		50	16.15	11.55	10.20	10.25	10.05	18.20	13.15	11.70	12.10	11.35	
		100	41.90	38.20	38.20	38.80	37.40	52.70	49.10	49.75	51.05	50.75		100	17.65	13.10	10.25	9.15	9.50	19.45	14.55	11.30	10.60	10.55	
		200	46.10	44.85	43.35	41.30	42.40	56.75	55.45	54.50	53.35	52.65		200	15.75	13.45	12.20	11.60	10.90	16.70	14.35	12.85	12.35	11.65	
Bartlett	$S^{(2)}_{n,T}$	10	34.40	30.75	32.05	30.30	30.65	45.80	43.75	44.90	43.20	43.30	$J^{(2)}_{n,T}$	10	17.35	12.10	11.10	10.20	9.10	24.35	17.15	16.95	15.20	14.75	
		20	29.90	28.85	28.05	26.35	26.80	42.85	41.00	41.60	40.80	40.55		20	15.75	7.25	5.05	5.15	4.20	22.35	12.65	9.30	8.65	8.00	
		30	37.00	35.45	35.20	36.00	34.55	50.10	48.10	47.50	47.10	46.90		30	17.90	8.40	6.45	5.80	4.20	25.20	13.25	10.75	9.15	7.05	
		50	48.05	48.80	45.25	47.20	45.75	58.95	59.15	56.20	57.25	57.35		50	22.55	11.00	8.75	7.75	6.85	29.45	15.35	11.90	11.25	9.50	
		100	56.90	52.95	53.40	55.55	55.80	66.60	63.25	64.45	65.60	65.40		100	33.55	13.45	8.70	7.30	5.45	41.35	17.10	11.95	9.90	7.45	
		200	64.30	63.25	61.45	60.20	60.10	71.60	71.40	70.75	68.70	68.55		200	53.40	18.05	12.55	7.70	5.75	61.65	22.85	15.95	10.45	7.70	
Parzen	$S^{(2)}_{n,T}$	10	34.40	30.75	32.05	30.30	30.65	45.80	43.75	44.90	43.20	43.30	$J^{(2)}_{n,T}$	10	17.35	12.10	11.10	10.20	9.10	24.35	17.15	16.95	15.20	14.75	
		20	38.95	37.55	38.15	38.30	37.45	51.50	49.85	50.45	49.00	49.65		20	16.90	10.55	7.65	7.80	7.40	22.10	15.65	12.45	12.40	11.25	
		30	46.60	45.15	45.20	44.85	44.80	59.25	57.90	57.15	55.15	56.00		30	16.85	11.75	9.85	9.05	7.45	22.55	15.70	14.00	12.90	10.40	
		50	56.75	57.60	54.70	55.90	55.55	65.50	65.75	64.95	65.50	66.10		50	22.05	14.25	12.10	11.50	10.60	26.25	17.65	15.50	14.75	14.05	
		100	63.75	59.90	60.55	62.20	62.35	71.65	68.35	69.45	70.45	70.85		100	27.65	14.05	10.65	9.80	7.65	31.95	18.05	14.35	12.75	10.95	
		200	70.85	70.70	70.05	67.60	67.05	76.90	77.10	77.35	76.05	75.05		200	33.85	16.70	13.85	10.65	9.10	39.00	20.65	17.10	13.50	11.90	
Tukey	$S^{(2)}_{n,T}$	10	34.40	30.75	32.05	30.30	30.65	45.80	43.75	44.90	43.20	43.30	$J^{(2)}_{n,T}$	10	17.35	12.10	11.10	10.20	9.10	24.35	17.15	16.95	15.20	14.75	
		20	31.05	29.95	29.65	27.90	27.85	44.20	42.40	42.80	41.95	41.90		20	17.05	7.70	5.70	5.55	5.00	23.70	13.25	10.05	9.45	8.75	
		30	38.25	37.25	36.30	37.40	36.30	51.60	49.70	48.85	48.05	48.40		30	19.20	9.55	7.35	6.40	4.80	27.50	14.30	11.95	9.85	7.80	
		50	49.45	49.85	47.00	48.50	47.40	60.00	60.55	57.85	58.05	58.90		50	24.70	12.15	9.45	8.85	7.55	31.80	16.60	13.25	11.95	10.70	
		100	57.00	53.35	53.75	55.75	56.10	66.75	63.35	64.70	65.95	65.55		100	57.85	19.40	13.05	10.10	7.00	67.60	25.20	18.25	14.20	10.55	
		200	65.65	64.50	62.55	61.50	61.30	72.30	72.15	71.70	69.35	69.55		200	87.60	38.75	23.65	14.00	10.55	90.35	48.20	30.20	18.75	14.00	
QS	$S^{(2)}_{n,T}$	10	31.15	27.50	27.80	27.50	27.55	43.65	41.20	41.75	40.05	40.35	$J^{(2)}_{n,T}$	10	15.30	10.20	9.05	8.15	7.50	22.10	15.50	14.75	13.20	12.20	
		20	25.85	23.15	22.90	21.75	21.90	37.85	35.75	35.55	35.30	35.05		20	25.70	9.45	6.40	5.45	4.10	36.70	17.15	11.60	9.60	8.95	
		30	31.80	30.90	30.05	30.30	29.15	45.35	43.20	42.45	42.15	42.10		30	33.35	11.70	8.40	6.30	4.45	44.95	18.60	14.50	11.20	7.90	
		50	43.75	43.25	40.65	41.75	40.90	55.05	55.80	52.55	53.75	53.05		50	44.40	16.60	11.00	8.55	7.00	55.00	24.45	17.40	14.35	11.55	
		100	51.80	48.55	49.00	50.05	50.10	63.55	59.35	60.05	61.20	61.70		100	88.15	30.50	18.05	11.25	6.95	93.15	41.50	26.45	17.25	11.50	
		200	58.60	58.00	56.30	56.05	54.75	68.25	68.10	66.70	64.90	64.40		200	100.00	71.25	38.90	18.90	11.90	100.00	80.80	50.35	26.65	16.75	
	$S^{(3)}_{n,T}$	10	3.65	2.65	1.70	1.75	1.05	9.60	7.65	6.90	6.30	5.45	$J^{(3)}_{n,T}$	10		44.00	20.45	9.25	3.25		58.60	35.35	18.65	10.60	
		20	4.00	2.00	1.70	1.80	1.70	9.95	7.30	6.10	6.35	6.05		20			81.00	35.45	9.95			88.55	52.95	24.00	
		30	3.40	1.65	1.45	1.40	1.20	8.90	6.60	6.00	5.95	4.95		30				83.50	28.70				91.65	46.75	
		50	4.00	2.05	1.40	1.95	0.90	9.80	6.95	5.95	6.65	5.70		50					82.70					91.95	
		100	3.70	2.85	1.80	1.80	1.20	10.25	7.30	5.75	6.05	5.25		100											
		200	3.80	1.85	1.70	1.25	1.45	10.25	7.50	7.00	5.70	4.65		200											
Fixed	$S^{(4)}_{n,T}$	10	0.40	0.60	0.60	0.80	0.80	3.70	4.75	4.85	5.30	4.70	$J^{(4)}_{n,T}$	10	0.70	1.55	2.40	2.70	2.80	5.65	8.35	10.95	10.85	9.75	
		20	0.15	0.35	0.60	1.10	1.30	4.35	4.25	4.20	5.15	5.55		20	1.05	0.85	1.40	1.85	1.60	6.50	6.35	8.10	7.70	8.35	
		30	0.20	0.45	0.60	1.05	1.00	3.80	4.00	4.20	5.15	4.30		30	1.20	1.45	1.45	2.40	2.05	6.95	6.05	6.85	7.95	8.35	
		50	0.20	0.70	0.55	1.20	0.65	4.30	4.50	4.25	5.55	5.10		50	2.15	1.00	1.20	1.05	1.70	8.65	5.40	6.45	5.85	6.65	
		100	0.05	1.00	0.80	1.20	1.05	4.25	5.30	4.75	5.50	4.75		100	4.95	1.30	1.25	1.00	0.65	14.50	6.35	6.30	6.55	4.80	
		200	0.15	0.75	0.70	0.90	1.35	4.40	5.05	5.25	4.75	4.35		200	10.85	2.45	1.40	1.20	1.00	23.60	9.35	7.50	6.40	5.55	
Expanding	$S^{(4)}_{n,T}$	10	0.30	0.60	0.60	0.80	0.80	3.65	4.70	4.70	5.20	4.60	$J^{(4)}_{n,T}$	10	0.80	1.80	1.95	2.40	2.70	4.70	7.45	8.35	8.75	8.25	
		20	0.15	0.35	0.60	1.10	1.30	4.35	4.25	4.20	5.15	5.55		20	1.05	0.85	1.40	1.85	1.60	6.50	6.35	8.10	7.70	8.35	
		30	0.20	0.45	0.60	1.05	1.00	3.80	4.00	4.20	5.15	4.30		30	1.20	1.45	1.45	2.40	2.05	6.95	6.05	6.85	7.95	8.35	
		50	0.20	0.70	0.55	1.20	0.65	4.30	4.50	4.25	5.55	5.10		50	2.15	1.00	1.20	1.05	1.70	8.65	5.40	6.45	5.85	6.65	
		100	0.05	1.00	0.80	1.20	1.05	4.30	5.30	4.75	5.50	4.75		100	9.70	1.95	1.50	1.15	0.80	22.25	8.50	7.45	6.70	6.00	
		200	0.15	0.75	0.70	0.90	1.35	4.40	5.05	5.25	4.75	4.35		200	21.40	4.45	2.45	1.65	0.90	30.95	11.95	9.30	7.60	6.05	
Fixed	$S^{(5)}_{n,T}$	10	0.40	0.80	0.65	0.85	0.85	3.75	4.95	5.15	5.30	4.75	$J^{(5)}_{n,T}$	10	4.80	1.80	1.95	2.40	2.70	10.15	7.90	9.55	9.70	8.95	
		20	0.15	0.35	0.60	1.15	1.50	4.35	4.30	4.30	5.20	5.70		20	5.30	9.90	3.70	1.15	1.45	7.25	17.30	10.10	6.05	7.25	
		30	0.20	0.45	0.65	1.05	1.00	3.80	4.05	4.25	5.20	4.40		30	6.95	11.85	8.50	1.55	1.45	9.15	18.15	17.20	7.40	8.25	
		50	0.20	0.75	0.55	1.20	0.65	4.35	4.50	4.25	5.55	5.10		50	7.90	15.40	14.25	0.95	0.95	9.85	21.00	25.00	6.55	6.20	
		100	0.05	1.00	0.80	1.20	1.05	4.25	5.30	4.75	5.50	4.75		100	6.65	17.45	22.95	1.25	0.95	8.35	22.25	33.05	7.65	4.15	
		200	0.15	0.75	0.70	0.90	1.35	4.40	5.05	5.25	4.75	4.35		200	4.35	12.30	20.80	32.35	1.05	4.70	14.30	24.25	44.35	6.30	
Expanding	$S^{(5)}_{n,T}$	10	0.30	0.65	0.65	0.85	0.80	3.75	4.75	4.85	5.30	4.70	$J^{(5)}_{n,T}$	10	4.85	2.80	2.85	2.60	2.40	9.40	8.90	8.95	9.00	7.60	
		20	0.15	0.35	0.60	1.15	1.50	4.35	4.30	4.30	5.20	5.70		20	5.30	9.90	3.70	1.15	1.45	7.25	17.30	10.10	6.05	7.25	
		30	0.20	0.45	0.65	1.05	1.00	3.80	4.05	4.25	5.20	4.40		30	6.95	11.85	8.50	1.55	1.45	9.15	18.15	17.20	7.40	8.25	
		50	0.20	0.75	0.55	1.20	0.65	4.35	4.50	4.25	5.55	5.10		50	7.90	15.40	14.25	0.95	0.95	9.85	21.00	25.00	6.55	6.20	
		100	0.05	1.05	0.80	1.20	1.05	4.30	5.30	4.75	5.50	4.75		100	5.60	17.55	22.50	1.70	0.80	6.30	22.75	33.10	7.45	4.35	
		200	0.15	0.75	0.70	0.90	1.35	4.40	5.05	5.25	4.75	4.35		200	3.20	12.05	21.30	34.70	1.05	3.50	13.15	24.70	46.10	7.10	

Table B4: Size – DGP 2: Factor Dependence, High Spatial Dependence

			Overall EPA Test												Joint EPA Test										
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S^{(1)}_{n,T}$	10	41.05	40.60	36.65	36.75	41.15	53.35	51.90	49.25	48.35	52.60	$J^{(1)}_{n,T}$	10	17.50	16.35	12.40	12.15	13.05	23.05	21.40	17.75	16.55	18.70
		20	54.55	54.50	54.55	52.20	51.15	65.10	64.40	64.45	62.25	61.05		20	22.35	19.30	18.35	16.10	15.15	27.75	24.20	22.35	20.60	19.65
		30	60.60	58.25	59.95	59.50	57.85	69.80	67.60	68.80	67.90	67.40		30	25.45	20.55	20.65	20.00	16.10	29.55	25.10	24.90	24.55	19.65
		50	67.60	66.80	65.30	68.65	67.30	75.55	74.60	73.65	75.05	74.75		50	28.85	23.40	21.00	20.85	18.65	33.20	26.80	24.50	24.80	21.95
		100	74.50	75.00	75.10	73.65	74.40	79.05	81.00	81.75	79.95	80.30		100	32.55	26.70	24.80	21.95	21.55	36.35	29.95	28.15	25.50	24.80
		200	79.65	81.30	81.05	81.25	81.55	85.05	85.25	85.70	85.35	85.70		200	36.15	28.70	26.10	26.20	24.35	38.50	31.35	28.10	28.80	26.85
Truncated	$S^{(2)}_{n,T}$	10	15.35	15.10	12.00	11.80	13.05	26.90	26.10	23.55	21.90	25.95	$J^{(2)}_{n,T}$	10	4.90	2.25	1.30	1.25	1.00	7.95	4.75	2.35	2.60	2.25
		20	12.25	10.30	9.80	9.05	8.65	22.35	22.05	20.65	18.40	17.95		20	3.30	2.85	3.20	2.85	2.65	4.55	3.55	4.10	3.60	3.50
		30	17.60	14.30	14.90	14.35	12.50	28.95	26.35	27.85	27.10	23.40		30	4.95	2.90	3.15	3.05	1.90	5.70	3.45	3.90	3.50	2.40
		50	25.10	23.30	21.75	21.80	19.50	36.95	34.80	34.05	34.70	33.30		50	5.20	3.60	2.75	3.45	2.70	6.20	4.30	3.45	3.75	3.15
		100	33.75	33.70	33.05	31.10	31.20	46.55	45.95	46.55	43.50	44.40		100	3.50	2.50	2.15	2.75	1.70	4.10	2.75	2.50	3.10	1.90
		200	38.95	37.05	37.40	36.80	37.30	50.35	49.50	49.30	49.30	50.15		200	6.65	5.85	4.70	5.50	5.75	7.35	6.15	5.20	5.90	6.20
Bartlett	$S^{(2)}_{n,T}$	10	41.05	40.60	36.65	36.75	41.15	53.35	51.90	49.25	48.35	52.60	$J^{(2)}_{n,T}$	10	17.50	16.35	12.40	12.15	13.05	23.05	21.40	17.75	16.55	18.70
		20	31.45	30.10	29.35	28.60	26.35	44.70	44.10	43.90	41.20	39.00		20	7.80	4.90	4.25	2.85	2.90	11.05	7.10	6.55	5.25	4.80
		30	38.40	35.25	37.55	36.95	33.95	50.75	49.05	49.90	48.60	46.45		30	9.75	4.45	4.65	3.75	2.95	12.85	6.55	6.75	5.60	4.70
		50	47.55	44.15	43.80	45.65	43.60	58.70	55.55	55.40	57.90	56.00		50	11.05	5.70	4.95	3.90	3.10	14.50	8.00	6.50	6.05	4.95
		100	51.05	50.75	51.25	48.45	50.10	62.15	61.05	61.55	59.65	61.75		100	10.50	4.15	2.60	2.35	1.35	13.05	5.45	3.80	3.40	2.50
		200	56.70	56.65	56.50	57.50	58.25	66.30	66.00	66.60	66.85	67.40		200	15.95	6.55	3.80	2.65	2.10	18.35	7.85	4.75	3.50	2.50
Parzen	$S^{(2)}_{n,T}$	10	41.05	40.60	36.65	36.75	41.15	53.35	51.90	49.25	48.35	52.60	$J^{(2)}_{n,T}$	10	17.50	16.35	12.40	12.15	13.05	23.05	21.40	17.75	16.55	18.70
		20	43.20	42.70	42.75	39.90	37.75	54.60	54.30	54.15	52.30	51.10		20	12.25	9.10	7.95	7.10	6.20	15.75	12.00	11.20	10.05	9.35
		30	49.50	48.20	48.90	47.75	45.45	60.30	57.70	59.75	58.70	57.30		30	14.15	8.65	9.25	7.75	7.00	17.55	11.40	12.40	10.45	9.15
		50	58.30	54.90	54.95	57.40	55.60	66.85	66.45	64.45	67.70	66.40		50	15.35	10.45	8.85	8.00	6.40	19.35	12.95	11.45	11.35	8.55
		100	58.75	57.65	58.35	56.35	57.80	67.55	66.90	67.25	66.30	66.75		100	11.65	6.15	4.65	4.40	3.80	13.70	8.30	5.85	5.65	5.05
		200	65.20	65.40	65.70	66.15	66.70	72.15	73.45	74.00	73.90	73.75		200	15.05	7.40	5.30	5.05	4.00	17.20	8.65	6.10	6.45	4.80
Tukey	$S^{(2)}_{n,T}$	10	41.05	40.60	36.65	36.75	41.15	53.35	51.90	49.25	48.35	52.60	$J^{(2)}_{n,T}$	10	17.50	16.35	12.40	12.15	13.05	23.05	21.40	17.75	16.55	18.70
		20	33.05	32.00	30.90	30.00	27.80	46.05	45.85	45.55	42.85	40.60		20	10.65	7.50	7.00	5.65	6.10	13.80	10.10	9.50	8.95	9.15
		30	39.85	36.55	38.90	38.45	36.20	52.10	50.35	51.55	50.10	48.20		30	12.95	6.45	6.70	5.50	4.90	16.45	9.15	9.80	7.70	7.15
		50	49.55	45.40	45.90	47.45	45.40	60.05	57.40	57.00	59.65	57.55		50	14.75	9.05	7.65	8.35	5.85	18.45	11.90	10.10	10.25	7.90
		100	51.30	50.95	51.45	48.65	50.30	62.30	61.10	61.70	59.85	61.85		100	25.30	19.30	14.30	14.90	14.60	29.05	22.40	16.95	17.10	17.70
		200	57.55	57.55	57.60	58.65	59.00	67.10	66.85	67.40	68.10	68.45		200	33.10	25.40	19.80	19.80	19.10	35.25	27.35	22.25	22.65	21.30
QS	$S^{(2)}_{n,T}$	10	36.30	35.80	32.55	31.75	36.35	49.05	48.10	45.50	44.25	48.40	$J^{(2)}_{n,T}$	10	14.35	12.60	9.25	9.15	9.45	19.05	17.65	14.00	13.30	14.50
		20	25.35	24.35	23.25	22.10	21.40	38.20	38.00	37.30	35.35	33.15		20	11.30	5.30	4.50	2.85	2.70	16.50	8.85	7.45	5.40	5.00
		30	32.20	29.50	31.65	30.80	27.80	44.15	42.40	43.50	42.85	41.55		30	15.45	6.10	5.90	3.80	3.35	21.40	9.25	8.85	6.75	5.55
		50	41.55	38.35	38.80	39.60	37.60	53.75	50.50	50.30	52.15	50.40		50	20.35	7.85	6.45	4.75	3.65	26.65	12.00	9.30	7.95	6.15
		100	45.05	45.25	45.65	42.75	43.75	57.10	56.15	56.45	54.65	56.20		100	35.10	10.05	5.55	4.80	3.25	42.95	13.90	8.80	6.20	5.25
		200	51.90	51.65	51.20	51.15	52.25	61.45	61.05	61.05	62.45	62.50		200	87.45	23.05	12.10	8.15	5.00	91.85	27.80	15.80	11.20	6.70
	$S^{(3)}_{n,T}$	10	4.45	2.75	1.45	1.75	1.30	9.75	8.90	5.85	5.70	5.75	$J^{(3)}_{n,T}$	10		43.00	20.15	8.95	4.35		56.85	34.15	18.60	10.60
		20	3.50	2.10	1.70	1.35	1.35	9.15	7.50	6.65	6.20	5.50		20			84.15	37.80	10.20			90.60	54.45	24.10
		30	4.55	1.95	1.90	1.20	1.15	9.40	6.20	7.20	5.85	5.60		30				83.80	26.65				91.30	45.45
		50	3.25	1.95	1.10	1.00	0.80	9.00	7.15	6.25	5.25	4.85		50					83.70					92.05
		100	3.05	1.65	1.05	1.85	0.70	8.60	6.85	5.60	5.90	5.15		100										
		200	3.60	1.90	1.75	1.40	1.75	9.70	6.85	6.15	6.15	5.40		200										
Fixed	$S^{(4)}_{n,T}$	10	0.10	0.70	0.70	0.90	1.15	4.80	5.95	4.10	4.95	5.40	$J^{(4)}_{n,T}$	10	4.65	5.75	6.20	6.25	7.60	11.40	13.20	12.60	13.00	15.25
		20	0.20	0.85	0.75	0.75	1.15	3.75	4.85	5.60	5.45	5.00		20	6.75	7.20	8.30	8.45	9.05	14.20	13.45	16.00	16.20	17.15
		30	0.40	0.55	0.80	0.80	1.00	4.85	4.05	5.55	5.05	5.15		30	8.00	8.85	9.55	9.80	10.05	16.30	16.40	16.85	16.85	17.20
		50	0.25	0.90	0.50	0.55	0.60	3.50	4.20	4.35	4.45	4.60		50	10.60	10.80	11.70	12.45	12.60	17.05	17.95	18.90	20.80	19.35
		100	0.05	0.65	0.40	1.25	0.50	3.40	4.20	4.25	5.20	4.75		100	16.20	14.90	15.80	16.05	17.00	23.55	21.35	23.70	23.75	24.00
		200	0.25	0.50	0.70	1.00	1.50	4.15	4.20	4.60	5.55	4.75		200	19.10	18.75	18.10	18.10	17.15	26.65	26.50	24.70	24.65	23.40
Expanding	$S^{(4)}_{n,T}$	10	0.10	0.65	0.70	0.85	1.15	4.70	5.80	4.05	4.85	5.20	$J^{(4)}_{n,T}$	10	4.95	5.95	6.45	6.75	6.95	12.70	13.00	14.00	13.30	14.30
		20	0.20	0.85	0.75	0.75	1.15	3.75	4.85	5.60	5.45	5.00		20	6.75	7.20	8.30	8.45	9.05	14.20	13.45	16.00	16.20	17.15
		30	0.40	0.55	0.80	0.80	1.00	4.85	4.05	5.55	5.05	5.15		30	8.00	8.85	9.55	9.80	10.05	16.30	16.40	16.85	16.85	17.20
		50	0.25	0.90	0.50	0.55	0.60	3.50	4.20	4.35	4.45	4.60		50	10.60	10.80	11.70	12.45	12.60	17.05	17.95	18.90	20.80	19.35
		100	0.05	0.70	0.45	1.25	0.55	3.40	4.20	4.25	5.20	4.75		100	18.45	14.05	15.95	16.15	16.60	26.55	21.55	24.00	22.95	22.95
		200	0.25	0.50	0.70	1.00	1.50	4.15	4.20	4.60	5.55	4.75		200	24.30	18.60	17.45	16.70	16.05	31.40	25.60	24.05	23.90	22.75
Fixed	$S^{(5)}_{n,T}$	10	0.10	0.65	0.70	0.90	1.15	4.80	5.80	4.10	4.90	5.35	$J^{(5)}_{n,T}$	10	4.50	7.20	7.60	9.00	9.30	9.20	13.10	14.20	14.40	16.20
		20	0.20	0.85	0.75	0.70	1.15	3.75	4.75	5.55	5.40	4.85		20	5.20	7.70	10.15	9.55	10.55	7.25	10.10	13.95	14.40	15.20
		30	0.40	0.55	0.75	0.70	1.00	4.75	3.90	5.40	4.85	5.05		30	4.75	7.25	8.85	10.80	12.75	6.25	9.10	10.85	13.85	16.15
		50	0.25	0.90	0.45	0.45	0.55	3.35	4.00	4.05	4.35	4.45		50	5.35	7.65	9.65	9.70	10.55	6.15	9.45	11.75	11.95	12.85
		100	0.00	0.55	0.40	1.15	0.45	3.25	3.90	3.80	4.70	4.30		100	4.05	6.40	5.80	6.75	6.75	4.55	7.35	6.30	7.80	7.10
		200	0.25	0.50	0.65	0.85	1.45	3.90	4.10	4.30	5.20	4.70		200	4.00	7.85	10.00	9.35	10.75	4.35	8.25	10.40	10.45	11.25
Expanding	$S^{(5)}_{n,T}$	10	0.10	0.65	0.65	0.85	1.15	4.70	5.75	3.90	4.80	5.20	$J^{(5)}_{n,T}$	10	4.60	5.95	7.20	6.95	8.40	7.30	9.15	10.15	11.50	13.15
		20	0.20	0.85	0.75	0.70	1.15	3.75	4.75	5.55	5.40	4.85		20	5.20	7.70	10.15	9.55	10.55	7.25	10.10	13.95	14.40	15.20
		30	0.40	0.55	0.75	0.70	1.00	4.75	3.90	5.40	4.85	5.05		30	4.75	7.25	8.85	10.80	12.75	6.25	9.10	10.85	13.85	16.15
		50	0.25	0.90	0.45	0.45	0.55	3.35	4.00	4.05	4.35	4.45		50	5.35	7.65	9.65	9.70	10.55	6.15	9.45	11.75	11.95	12.85
		100	0.00	0.60	0.40	1.20	0.50	3.25	4.00	4.00	4.70	4.40		100	4.60	7.00	7.90	10.40	10.20	5.30	7.95	8.45	11.50	11.15
		200	0.25	0.50	0.65	0.90	1.50	4.00	4.20	4.35	5.25	4.70		200	3.80	8.00	10.10	13.45	13.60	4.10	9.00	10.90	14.65	15.00

Table B5: Power Under Homogeneous Alternative – DGP 1: No Factor Dependence, No Spatial Dependence

			Overall EPA Test												Joint EPA Test										
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	0.75	10.00	15.90	29.55	61.30	15.10	25.35	35.20	51.95	82.15	$J_{n,T}^{(1)}$	10	7.40	4.45	6.00	8.80	22.40	19.90	15.25	18.45	24.75	45.40
		20	10.55	21.75	35.35	61.95	93.05	27.15	44.30	59.25	81.10	98.15		20	14.45	7.70	10.20	16.70	43.55	33.15	23.20	26.35	37.40	68.05
		30	14.35	36.85	55.20	82.30	99.30	35.35	60.90	77.60	94.50	99.90		30	19.75	11.65	13.20	23.55	61.40	41.15	30.80	31.55	47.55	83.30
		50	29.50	60.10	83.10	97.15	100.00	52.00	80.80	94.85	99.20	100.00		50	31.35	17.95	22.95	36.70	81.90	56.10	38.70	44.80	61.60	94.15
		100	61.15	93.05	99.15	100.00	100.00	82.75	98.15	100.00	100.00	100.00		100	56.00	36.65	43.25	69.10	98.30	78.55	62.45	68.00	86.70	99.65
		200	92.60	99.95	100.00	100.00	100.00	97.90	100.00	100.00	100.00	100.00		200	89.00	67.60	71.10	93.60	100.00	96.30	85.55	88.90	98.20	100.00
Truncated	$S_{n,T}^{(2)}$	10	6.45	10.95	16.05	29.90	61.70	17.25	26.55	36.00	51.75	82.30	$J_{n,T}^{(2)}$	10	32.25	14.75	11.50	12.10	25.05	44.25	30.30	26.70	29.55	48.25
		20	13.45	23.95	37.30	62.30	93.20	29.95	44.80	59.95	81.45	98.25		20	35.90	49.60	51.45	38.65	54.75	40.70	57.90	66.95	58.00	76.15
		30	17.40	38.75	56.45	82.60	99.20	37.45	61.60	78.05	94.30	99.95		30	37.50	50.60	66.85	58.45	74.90	42.50	57.80	77.80	77.95	90.00
		50	31.70	61.10	82.65	96.90	100.00	52.65	80.90	94.90	99.10	100.00		50	36.70	56.90	74.20	77.90	91.95	40.15	61.85	79.40	90.35	97.20
		100	62.20	93.50	99.15	100.00	100.00	82.80	98.15	99.95	100.00	100.00		100	40.25	58.55	83.60	98.65	99.70	41.95	61.15	84.75	99.70	99.95
		200	92.75	100.00	100.00	100.00	100.00	97.90	100.00	100.00	100.00	100.00		200	32.80	44.30	56.40	84.35	100.00	33.95	46.10	57.80	85.20	100.00
Bartlett	$S_{n,T}^{(2)}$	10	5.20	10.00	15.90	29.55	61.30	15.10	25.35	35.20	51.95	82.15	$J_{n,T}^{(2)}$	10	7.40	4.45	6.00	8.80	22.40	19.90	15.25	18.45	24.75	45.40
		20	11.50	21.60	35.55	62.20	93.25	28.00	44.25	59.80	81.55	98.10		20	26.05	12.30	12.70	18.35	44.90	47.50	30.40	30.45	39.50	68.90
		30	14.55	37.65	55.45	82.45	99.20	35.85	61.45	77.60	94.60	99.95		30	36.75	18.05	17.30	26.15	62.65	59.65	38.85	36.50	51.15	84.25
		50	30.35	60.65	82.85	96.95	100.00	52.20	80.70	94.70	99.20	100.00		50	57.15	27.45	29.15	41.05	83.80	75.50	50.85	53.75	66.55	94.50
		100	62.10	93.00	99.20	100.00	100.00	82.65	98.15	99.95	100.00	100.00		100	96.15	69.60	64.05	78.90	99.05	98.85	85.80	83.45	92.10	99.80
		200	92.85	99.95	100.00	100.00	100.00	97.95	100.00	100.00	100.00	100.00		200	100.00	97.55	94.10	98.00	100.00	100.00	99.45	97.90	99.60	100.00
Parzen	$S_{n,T}^{(2)}$	10	5.20	10.00	15.90	29.55	61.30	15.10	25.35	35.20	51.95	82.15	$J_{n,T}^{(2)}$	10	7.40	4.45	6.00	8.80	22.40	19.90	15.25	18.45	24.75	45.40
		20	10.95	21.90	35.55	62.30	93.15	27.30	44.35	59.65	81.25	98.10		20	16.40	8.30	10.85	16.65	43.70	35.55	25.35	27.90	37.80	68.20
		30	14.55	37.35	55.40	82.50	99.30	35.60	61.20	77.40	94.45	99.90		30	22.80	12.85	13.95	24.45	62.00	45.05	32.75	31.85	48.45	83.40
		50	29.90	60.30	83.15	97.10	100.00	51.90	80.70	94.80	99.20	100.00		50	36.10	19.95	24.15	37.55	82.60	60.25	41.05	46.35	63.10	94.25
		100	61.60	93.10	99.20	100.00	100.00	82.65	98.15	99.95	100.00	100.00		100	84.95	52.80	54.85	74.35	99.00	94.10	75.45	77.30	89.70	99.75
		200	92.60	99.95	100.00	100.00	100.00	97.95	100.00	100.00	100.00	100.00		200	99.50	86.70	84.95	96.35	100.00	99.75	96.00	94.80	99.10	100.00
Tukey	$S_{n,T}^{(2)}$	10	5.20	10.00	15.90	29.55	61.30	15.10	25.35	35.20	51.95	82.15	$J_{n,T}^{(2)}$	10	7.40	4.45	6.00	8.80	22.40	19.90	15.25	18.45	24.75	45.40
		20	11.40	21.60	35.50	62.10	93.30	27.85	44.25	60.05	81.50	98.10		20	24.75	11.65	12.30	18.00	44.60	45.95	29.60	30.05	39.05	68.75
		30	14.65	37.60	55.60	82.40	99.20	35.60	61.45	77.65	94.60	99.95		30	35.15	17.15	16.85	25.95	62.65	57.95	38.00	35.60	50.75	83.95
		50	30.45	60.55	83.00	96.95	100.00	52.15	80.65	94.70	99.20	100.00		50	54.90	26.15	28.20	40.55	83.80	73.50	49.55	52.60	66.20	94.50
		100	61.80	93.10	99.20	100.00	100.00	82.55	98.15	99.95	100.00	100.00		100	98.10	72.70	66.70	79.60	99.10	99.50	87.90	84.90	92.65	99.85
		200	92.80	99.95	100.00	100.00	100.00	97.95	100.00	100.00	100.00	100.00		200	100.00	98.15	94.55	98.05	100.00	100.00	99.60	98.10	99.65	100.00
QS	$S_{n,T}^{(2)}$	10	5.10	10.00	15.75	29.50	61.05	15.20	25.40	35.55	52.25	81.95	$J_{n,T}^{(2)}$	10	7.55	4.50	6.10	8.75	22.30	20.25	15.45	18.65	24.50	45.25
		20	11.90	21.65	36.30	62.30	93.30	28.45	44.60	59.65	81.70	98.25		20	43.25	18.60	16.50	21.05	46.45	63.40	36.70	34.40	42.50	69.65
		30	14.95	37.75	55.65	82.70	99.15	36.40	61.30	77.90	94.60	99.95		30	59.40	27.10	21.85	30.60	64.70	77.00	47.90	43.50	55.75	85.45
		50	30.50	60.75	82.60	96.85	100.00	52.05	80.65	94.90	99.20	100.00		50	81.85	41.25	38.15	46.40	85.40	92.20	63.85	63.30	70.60	94.95
		100	62.10	93.05	99.15	100.00	100.00	82.70	98.20	99.95	100.00	100.00		100	99.90	89.20	79.70	84.95	99.20	100.00	96.05	91.85	94.95	99.85
		200	92.80	99.95	100.00	100.00	100.00	97.90	100.00	100.00	100.00	100.00		200	100.00	99.90	99.25	99.60	100.00	100.00	100.00	99.85	99.90	100.00
	$S_{n,T}^{(3)}$	10	9.60	13.10	18.75	31.40	61.55	20.75	28.70	36.50	53.05	82.25	$J_{n,T}^{(3)}$	10		47.45	30.80	22.25	31.35		63.30	50.10	41.50	54.35
		20	17.50	26.40	38.20	62.85	93.50	33.50	46.85	61.40	81.95	98.25		20			90.60	67.55	68.60			95.25	81.10	85.50
		30	23.00	41.80	57.80	82.85	99.25	42.95	62.20	79.35	94.10	99.95		30				97.55	92.85				99.05	97.40
		50	38.15	63.30	83.00	97.10	100.00	57.35	82.05	94.75	99.25	100.00		50					99.95					100.00
		100	66.80	92.65	98.95	100.00	100.00	84.10	97.95	99.85	100.00	100.00		100										
		200	92.25	100.00	100.00	100.00	100.00	97.75	100.00	100.00	100.00	100.00		200										
Fixed	$S_{n,T}^{(4)}$	10	1.85	6.45	12.20	25.40	57.80	12.00	22.60	33.15	49.70	80.85	$J_{n,T}^{(4)}$	10	0.55	1.35	2.90	6.85	20.95	4.50	7.55	13.95	21.60	45.35
		20	4.85	15.15	30.00	56.85	92.20	21.55	40.15	57.35	80.20	98.05		20	1.05	1.35	2.70	8.35	32.40	6.70	8.30	12.75	25.00	59.70
		30	7.45	28.05	50.00	79.95	99.10	28.95	57.40	75.50	93.65	99.90		30	0.90	1.75	3.80	9.50	44.90	6.30	8.90	13.50	28.20	71.35
		50	15.85	51.85	78.35	96.70	100.00	44.35	77.80	93.85	99.10	100.00		50	1.65	1.95	3.95	13.75	56.45	7.75	8.65	16.00	32.15	79.95
		100	41.65	88.35	98.60	100.00	100.00	76.20	97.55	99.90	100.00	100.00		100	3.45	3.60	6.30	18.90	67.25	11.50	10.85	17.70	39.65	83.60
		200	79.50	100.00	100.00	100.00	100.00	95.85	100.00	100.00	100.00	100.00		200	8.10	5.60	7.95	20.50	40.20	16.30	14.05	19.45	34.50	53.00
Expanding	$S_{n,T}^{(4)}$	10	2.60	7.00	13.00	26.50	58.65	12.90	23.80	33.50	50.15	81.00	$J_{n,T}^{(4)}$	10	0.45	1.25	2.10	5.55	18.70	3.60	6.60	10.60	18.40	43.50
		20	4.85	15.15	30.00	56.85	92.20	21.55	40.15	57.35	80.20	98.05		20	1.05	1.35	2.70	8.35	32.40	6.70	8.30	12.75	25.00	59.70
		30	7.45	28.05	50.00	79.95	99.10	28.95	57.40	75.50	93.65	99.90		30	0.90	1.75	3.80	9.50	44.90	6.30	8.90	13.50	28.20	71.35
		50	15.85	51.85	78.35	96.70	100.00	44.35	77.80	93.85	99.10	100.00		50	1.65	1.95	3.95	13.75	56.45	7.75	8.65	16.00	32.15	79.95
		100	35.20	86.40	98.45	100.00	100.00	74.00	97.65	99.90	100.00	100.00		100	6.15	3.15	4.30	12.95	55.20	14.00	8.90	12.95	30.80	76.35
		200	74.10	99.95	100.00	100.00	100.00	95.25	100.00	100.00	100.00	100.00		200	9.85	5.10	4.65	11.80	26.00	16.40	11.10	12.35	21.20	38.30
Fixed	$S_{n,T}^{(5)}$	10	1.40	6.20	11.85	25.10	57.40	11.40	22.50	32.55	49.70	80.70	$J_{n,T}^{(5)}$	10	3.55	1.10	1.60	5.25	19.00	7.35	6.60	11.40	18.75	43.85
		20	3.70	13.40	29.15	56.15	92.45	19.70	39.40	57.30	80.05	98.15		20	5.50	8.75	3.55	4.40	28.00	7.80	15.15	12.90	19.20	55.10
		30	5.80	26.75	47.55	79.55	98.90	27.45	57.05	75.10	93.35	99.90		30	6.45	11.20	7.95	6.25	37.80	8.45	17.15	18.20	23.40	67.80
		50	13.90	50.85	77.60	96.15	100.00	45.00	77.30	93.45	99.15	100.00		50	6.65	13.55	14.05	9.55	49.85	8.35	18.20	27.00	26.75	77.60
		100	39.50	87.45	98.60	100.00	100.00	75.80	97.60	99.90	100.00	100.00		100	6.65	16.95	21.90	11.40	57.20	7.80	21.05	32.15	29.10	78.65
		200	78.30	100.00	100.00	100.00	100.00	95.80	100.00	100.00	100.00	100.00		200	3.55	10.75	16.60	32.95	29.40	3.75	11.70	19.15	42.40	42.05
Expanding	$S_{n,T}^{(5)}$	10	3.80	8.80	16.85	30.40	63.25	15.30	27.15	37.60	54.00	84.20	$J_{n,T}^{(5)}$	10	7.00	4.05	7.15	11.85	30.85	15.05	14.65	21.20	30.25	55.50
		20	6.65	19.00	35.50	63.10	93.85	24.45	44.10	61.70	83.45	98.55		20	7.95	18.05	16.20	20.85	52.00	11.80	29.80	35.60	44.40	76.70
		30	9.20	33.75	55.80	83.90	99.35	33.75	61.30	79.30	94.55	99.90		30	10.45	20.65	26.35	32.15	71.25	13.50	30.80	46.75	57.80	88.70
		50	19.15	58.05	82.35	97.20	100.00	48.70	80.90	95.20	99.20	100.00		50	10.15	24.95	40.65	45.45	85.90	13.15	33.75	57.50	70.25	95.60
		100	40.15	89.50	98.90	100.00	100.00	77.00	98.25	99.95	100.00	100.00		100	9.60	27.75	50.05	56.15	89.45	11.05	33.25	61.70	75.15	96.50
		200	77.90	99.95	100.00	100.00	100.00	96.15	100.00	100.00	100.00	100.00		200	5.30	16.45	31.20	62.05	70.95	5.95	18.55	34.65	68.50	81.75

Table B6: Power Under Homogeneous Alternative – DGP 1: No Factor Dependence, Low Spatial Dependence

			Overall EPA Test												Joint EPA Test									
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S^{(1)}_{n,T}$	10	8.65	14.75	20.05	34.85	59.35	21.95	32.10	37.60	54.45	76.15	$J^{(1)}_{n,T}$	10	8.50	5.70	6.00	11.65	23.80	22.35	16.60	18.65	26.10	44.50
		20	13.10	27.85	41.00	60.00	88.40	28.95	47.60	59.85	78.10	95.70		20	13.40	9.30	10.95	18.45	44.35	30.00	24.45	26.80	38.35	64.50
		30	20.70	39.60	53.75	76.20	97.50	38.05	59.30	74.10	89.25	99.45		30	19.75	13.20	14.35	24.15	58.25	39.45	29.45	32.40	46.20	77.25
		50	34.15	59.00	78.65	94.25	99.95	52.80	77.00	90.70	98.50	100.00		50	31.55	18.30	23.15	38.30	78.75	55.40	39.10	45.70	60.15	91.65
		100	59.95	89.95	97.30	99.95	100.00	76.95	95.95	99.25	100.00	100.00		100	58.55	37.25	43.15	65.45	97.55	78.45	60.90	67.10	83.75	99.45
		200	88.75	99.70	100.00	100.00	100.00	96.20	99.90	100.00	100.00	100.00		200	87.10	66.25	73.65	92.50	100.00	95.80	85.30	88.85	98.60	100.00
Truncated	$S^{(2)}_{n,T}$	10	4.15	7.00	10.00	19.80	42.25	13.65	21.55	26.00	41.25	65.75	$J^{(2)}_{n,T}$	10	27.50	15.45	11.40	9.70	15.35	37.40	27.95	24.65	24.45	33.90
		20	8.10	16.05	25.20	41.70	77.55	19.80	35.10	47.95	66.40	91.05		20	32.25	40.55	46.80	30.65	34.60	37.70	50.20	63.10	50.95	57.70
		30	11.80	24.10	37.50	61.20	92.95	28.05	47.10	62.00	82.15	98.45		30	33.50	44.25	56.85	47.55	50.40	38.25	51.95	67.70	67.35	72.05
		50	21.60	42.65	64.60	87.90	99.80	41.60	66.30	84.45	96.35	100.00		50	37.20	51.45	67.25	68.40	73.15	40.65	56.10	73.05	84.30	88.10
		100	41.40	78.15	92.15	99.60	100.00	65.15	92.30	98.10	99.95	100.00		100	40.80	54.65	75.15	94.35	96.05	42.05	57.10	77.40	97.95	98.80
		200	79.40	98.55	100.00	100.00	100.00	92.10	99.85	100.00	100.00	100.00		200	33.20	42.25	54.80	78.70	100.00	34.25	43.95	56.50	79.80	100.00
Bartlett	$S^{(2)}_{n,T}$	10	8.65	14.75	20.05	34.85	59.35	21.95	32.10	37.60	54.45	76.15	$J^{(2)}_{n,T}$	10	8.50	5.70	6.00	11.65	23.80	22.35	16.60	18.65	26.10	44.50
		20	9.60	21.30	33.30	51.20	82.95	23.55	41.35	54.60	72.95	94.05		20	20.10	9.30	9.75	13.60	32.35	38.85	25.55	24.60	32.75	55.95
		30	15.15	30.85	45.45	70.15	95.70	33.40	52.65	68.50	86.40	99.05		30	30.55	14.70	12.85	18.10	47.15	51.00	30.50	30.75	40.20	69.95
		50	27.65	51.60	72.85	92.20	99.90	47.70	72.40	88.65	97.75	100.00		50	48.45	21.25	22.05	30.45	69.30	70.25	42.25	43.90	53.55	85.05
		100	47.85	82.55	94.55	99.75	100.00	68.85	94.10	98.45	99.95	100.00		100	92.65	53.90	47.00	55.55	91.80	97.65	75.85	70.30	78.05	97.55
		200	83.45	99.25	100.00	100.00	100.00	93.90	99.85	100.00	100.00	100.00		200	99.95	92.55	86.60	91.45	99.95	100.00	97.95	95.70	98.20	100.00
Parzen	$S^{(2)}_{n,T}$	10	8.65	14.75	20.05	34.85	59.35	21.95	32.10	37.60	54.45	76.15	$J^{(2)}_{n,T}$	10	8.50	5.70	6.00	11.65	23.80	22.35	16.60	18.65	26.10	44.50
		20	11.15	24.85	37.60	55.55	86.10	26.10	44.55	57.05	75.65	94.95		20	13.70	8.40	9.40	15.35	37.20	29.30	22.30	24.05	34.50	59.75
		30	17.60	35.40	49.60	73.70	96.75	35.85	56.00	71.05	87.60	99.35		30	20.00	11.80	12.15	19.85	52.25	39.55	27.20	29.50	42.05	73.10
		50	30.75	55.10	76.15	93.05	99.95	50.30	75.20	89.75	98.25	100.00		50	32.50	16.45	19.75	32.65	74.05	55.30	36.75	41.45	54.95	88.40
		100	50.35	84.40	95.15	99.85	100.00	70.90	94.70	98.60	99.95	100.00		100	75.75	39.90	37.75	52.25	92.45	90.15	62.60	62.75	75.45	97.70
		200	84.60	99.45	100.00	100.00	100.00	94.40	99.85	100.00	100.00	100.00		200	98.15	76.05	74.00	87.45	99.90	99.45	90.30	89.40	96.55	100.00
Tukey	$S^{(2)}_{n,T}$	10	8.65	14.75	20.05	34.85	59.35	21.95	32.10	37.60	54.45	76.15	$J^{(2)}_{n,T}$	10	8.50	5.70	6.00	11.65	23.80	22.35	16.60	18.65	26.10	44.50
		20	9.45	21.30	33.40	51.60	83.00	23.65	41.40	54.75	72.95	94.15		20	18.60	9.05	9.40	13.70	32.55	37.60	24.70	24.25	32.65	55.95
		30	15.15	31.15	45.75	70.30	95.80	33.60	53.00	68.75	86.45	99.05		30	29.25	13.90	12.35	17.75	47.50	49.55	30.15	29.85	40.00	70.00
		50	27.70	51.75	72.95	92.20	99.90	47.55	72.60	88.75	97.75	100.00		50	46.45	20.20	21.55	30.15	69.25	67.90	41.45	43.60	53.35	85.00
		100	46.55	82.00	94.10	99.75	100.00	68.30	93.90	98.35	99.95	100.00		100	95.65	58.15	49.05	56.20	91.50	98.45	79.00	71.90	78.50	97.40
		200	82.70	99.05	100.00	100.00	100.00	93.65	99.85	100.00	100.00	100.00		200	100.00	94.15	88.00	91.60	99.90	100.00	98.80	96.25	98.35	100.00
QS	$S^{(2)}_{n,T}$	10	8.05	13.50	18.50	32.60	56.60	20.65	30.30	35.75	53.15	75.00	$J^{(2)}_{n,T}$	10	7.90	5.20	5.25	10.05	21.90	21.15	15.50	17.25	24.10	41.45
		20	8.25	18.60	29.80	47.65	81.35	22.05	38.70	52.35	70.75	93.15		20	35.05	12.75	12.05	13.95	30.80	55.65	31.35	27.15	32.90	54.25
		30	13.40	28.45	42.75	67.40	94.75	30.80	50.55	66.05	85.05	98.85		30	51.15	21.20	16.20	19.70	45.05	69.55	40.70	35.55	41.55	68.70
		50	25.45	47.90	70.20	90.70	99.85	45.00	70.20	87.50	97.50	100.00		50	77.00	32.80	28.15	32.45	66.85	90.15	55.75	50.85	55.80	83.75
		100	44.75	80.30	93.05	99.70	100.00	66.55	93.10	98.30	99.95	100.00		100	99.85	80.30	65.20	64.20	92.00	100.00	92.25	83.00	83.70	97.25
		200	81.55	98.85	100.00	100.00	100.00	92.90	99.85	100.00	100.00	100.00		200	100.00	99.95	97.50	97.40	99.95	100.00	100.00	99.20	99.50	100.00
	$S^{(3)}_{n,T}$	10	6.15	8.10	10.85	19.15	39.65	16.20	21.65	25.15	39.20	63.60	$J^{(3)}_{n,T}$	10		44.95	24.60	17.30	17.70		61.60	41.75	34.45	36.20
		20	12.40	18.20	26.35	42.75	77.50	23.75	36.60	48.90	66.35	90.50		20			88.00	60.10	49.05			93.60	76.45	70.15
		30	17.05	27.50	39.45	61.45	92.35	31.60	48.80	62.95	82.00	98.25		30				94.55	78.40				97.65	90.10
		50	27.70	45.70	65.35	87.00	99.75	47.40	67.65	84.70	96.30	99.95		50					99.45					99.85
		100	50.25	78.70	92.00	99.60	100.00	68.70	92.20	97.95	99.90	100.00		100										
		200	79.95	98.65	99.95	100.00	100.00	92.50	99.65	100.00	100.00	100.00		200										
Fixed	$S^{(4)}_{n,T}$	10	0.95	4.15	4.85	11.65	26.50	7.75	15.20	20.05	32.50	54.05	$J^{(4)}_{n,T}$	10	0.60	1.10	2.15	4.25	10.05	5.25	7.50	9.70	15.65	24.80
		20	3.25	11.30	19.35	36.35	71.80	16.05	32.30	45.70	63.45	88.65		20	0.60	1.10	2.55	5.05	15.95	6.00	7.75	9.75	17.45	37.50
		30	5.60	19.65	34.40	59.10	91.05	22.05	45.70	61.70	82.20	98.05		30	1.05	1.50	2.95	6.15	22.35	5.95	8.15	11.55	21.00	47.75
		50	13.10	40.65	64.00	87.55	99.75	37.75	67.70	85.70	97.20	100.00		50	2.05	1.70	3.90	9.45	35.20	8.40	8.15	13.20	24.35	59.50
		100	33.20	77.05	93.50	99.85	100.00	64.00	92.60	98.30	99.95	100.00		100	4.45	3.30	5.30	13.35	41.50	11.25	11.65	14.80	29.65	62.20
		200	66.95	98.30	100.00	100.00	100.00	91.60	99.85	100.00	100.00	100.00		200	8.15	5.05	7.25	15.75	24.95	15.20	11.95	15.90	26.90	36.85
Expanding	$S^{(4)}_{n,T}$	10	2.40	6.60	8.40	16.10	33.85	10.80	18.40	23.90	36.45	58.80	$J^{(4)}_{n,T}$	10	0.40	1.15	1.80	4.60	10.20	4.05	6.00	8.90	15.45	26.35
		20	3.25	11.30	19.35	36.35	71.80	16.05	32.30	45.70	63.45	88.65		20	0.60	1.10	2.55	5.05	15.95	6.00	7.75	9.75	17.45	37.50
		30	5.60	19.65	34.40	59.10	91.05	22.05	45.70	61.70	82.20	98.05		30	1.05	1.50	2.95	6.15	22.35	5.95	8.15	11.55	21.00	47.75
		50	13.10	40.65	64.00	87.55	99.75	37.75	67.70	85.70	97.20	100.00		50	2.05	1.70	3.90	9.45	35.20	8.40	8.15	13.20	24.35	59.50
		100	26.90	73.50	91.75	99.70	100.00	60.65	92.00	98.05	99.95	100.00		100	5.65	3.60	3.20	8.80	29.60	12.75	9.90	10.85	20.60	50.60
		200	59.20	97.80	100.00	100.00	100.00	89.90	99.80	100.00	100.00	100.00		200	10.50	3.85	4.15	7.75	14.10	16.30	9.65	10.45	15.60	25.00
Fixed	$S^{(5)}_{n,T}$	10	0.80	3.55	4.80	12.15	29.25	7.30	15.40	20.25	33.05	55.95	$J^{(5)}_{n,T}$	10	4.30	1.25	1.60	2.95	8.70	8.90	6.60	7.30	12.55	23.05
		20	1.55	9.05	17.35	33.60	71.70	14.05	29.40	42.85	62.10	88.80		20	5.55	9.80	4.95	2.70	10.95	8.00	15.85	11.60	13.40	32.20
		30	2.95	15.05	27.85	53.60	89.45	19.10	41.35	57.25	79.65	97.50		30	6.00	11.80	10.00	3.20	14.30	7.75	16.80	20.40	14.55	37.40
		50	9.05	31.45	55.80	83.30	99.55	32.25	62.55	81.25	95.65	100.00		50	6.75	11.55	16.00	4.70	17.85	8.25	16.10	24.90	16.80	43.95
		100	22.45	67.50	88.70	99.45	100.00	57.05	89.45	97.35	99.90	100.00		100	6.35	15.20	20.70	5.45	16.05	7.25	19.90	29.05	16.70	36.30
		200	56.95	96.45	99.95	100.00	100.00	87.75	99.65	100.00	100.00	100.00		200	3.10	10.60	16.15	26.45	8.30	3.40	12.10	19.00	34.40	16.75
Expanding	$S^{(5)}_{n,T}$	10	2.10	5.95	7.50	15.85	34.00	10.80	18.05	23.20	36.50	58.60	$J^{(5)}_{n,T}$	10	7.60	3.65	4.85	7.10	13.10	15.40	14.40	15.75	21.30	31.75
		20	2.95	11.55	20.90	38.20	74.60	16.55	32.80	46.30	64.75	90.45		20	9.00	15.45	12.00	13.45	26.80	13.00	25.05	28.15	32.35	51.55
		30	5.35	19.30	33.65	58.30	91.60	21.60	45.35	61.40	82.00	98.00		30	9.50	17.10	22.10	18.55	38.60	12.60	27.50	39.10	42.85	64.65
		50	12.00	37.85	61.90	86.15	99.70	37.15	65.75	84.60	96.70	100.00		50	10.05	22.50	35.25	29.10	55.90	12.70	30.25	50.00	54.25	78.60
		100	23.20	69.30	90.30	99.65	100.00	58.55	90.85	97.75	99.95	100.00		100	8.25	24.85	39.55	36.80	53.50	9.10	29.40	49.55	57.55	75.35
		200	56.40	97.15	99.95	100.00	100.00	88.85	99.60	100.00	100.00	100.00		200	6.05	15.20	28.55	50.40	42.45	6.80	17.55	31.65	57.75	59.55

Table B7: Power Under Homogeneous Alternative – DGP 1: No Factor Dependence, High Spatial Dependence

Overall EPA Test

Option	Test	$n\backslash T$	1% Nominal Size 10	20	30	50	100	5% Nominal Size 10	20	30	50	100
	$S_{n,T}^{(1)}$	10	39.60	39.70	41.55	48.85	56.30	52.70	52.25	54.95	61.00	67.50
		20	45.40	48.70	52.25	57.20	71.70	58.25	59.35	64.50	66.95	79.30
		30	46.75	51.00	54.05	64.30	78.20	57.80	61.50	65.00	72.30	84.05
		50	48.85	57.30	64.70	75.10	90.55	60.70	68.25	74.25	81.50	93.80
		100	57.70	72.25	81.00	91.40	99.10	67.75	80.65	86.30	94.65	99.60
		200	71.55	86.70	93.50	98.55	99.95	78.95	90.40	95.85	99.20	100.00
Truncated	$S_{n,T}^{(2)}$	10	10.35	12.15	13.45	17.05	24.55	24.35	24.00	26.10	32.85	41.00
		20	7.05	8.40	10.90	14.35	26.20	17.05	20.35	24.80	29.50	43.95
		30	6.65	9.75	13.80	19.30	35.55	18.80	22.85	26.75	36.20	53.60
		50	10.80	14.40	20.05	31.35	55.35	23.00	28.85	36.15	50.90	73.95
		100	8.35	18.00	30.15	49.05	81.45	22.20	37.40	51.30	70.35	92.90
		200	16.60	34.05	51.60	76.45	97.35	34.55	55.80	72.30	90.50	99.45
Bartlett	$S_{n,T}^{(2)}$	10	39.60	39.70	41.55	48.85	56.30	52.70	52.25	54.95	61.00	67.50
		20	22.75	25.80	30.20	37.20	51.35	37.30	40.50	43.75	49.95	64.05
		30	24.55	29.00	33.65	43.70	60.80	38.55	42.20	47.80	56.70	72.50
		50	28.35	35.90	43.40	57.60	79.15	42.20	49.05	56.95	69.75	88.00
		100	22.65	37.95	52.35	71.25	93.10	39.50	55.80	68.70	83.55	97.45
		200	37.35	60.35	75.45	92.25	99.60	53.85	75.55	86.05	95.80	99.95
Parzen	$S_{n,T}^{(2)}$	10	39.60	39.70	41.55	48.85	56.30	52.70	52.25	54.95	61.00	67.50
		20	33.75	37.45	40.85	47.65	62.40	47.05	50.45	54.10	58.45	72.30
		30	35.65	39.20	44.20	54.10	70.75	48.80	52.80	55.40	65.25	79.10
		50	39.90	46.65	54.55	67.75	86.50	51.35	58.95	65.95	76.45	91.10
		100	31.50	47.55	60.40	78.45	95.95	47.25	64.05	74.25	87.40	98.15
		200	48.10	70.45	82.85	94.75	99.85	62.70	81.65	90.15	97.55	99.95
Tukey	$S_{n,T}^{(2)}$	10	39.60	39.70	41.55	48.85	56.30	52.70	52.25	54.95	61.00	67.50
		20	24.00	27.60	31.50	38.75	52.60	39.00	41.50	45.05	51.50	65.30
		30	25.70	30.00	35.00	45.10	62.00	39.70	43.30	48.95	58.00	73.50
		50	29.50	37.35	44.70	59.20	80.30	42.60	50.05	58.60	70.40	88.30
		100	22.00	37.20	51.20	70.35	93.05	39.00	55.30	68.20	83.25	97.40
		200	37.65	60.55	75.60	92.30	99.65	53.85	75.75	86.10	95.90	99.95
QS	$S_{n,T}^{(2)}$	10	34.95	34.75	36.15	43.45	52.05	48.75	48.00	50.75	56.60	64.75
		20	16.75	19.80	24.60	29.40	43.85	30.45	33.85	37.95	44.55	58.95
		30	17.80	22.25	26.20	36.20	53.60	31.90	36.15	41.00	50.95	67.60
		50	22.30	28.20	35.80	50.40	74.10	36.75	43.65	51.10	64.65	84.60
		100	16.05	29.85	43.05	63.95	89.50	32.60	48.45	61.00	79.00	96.25
		200	28.90	50.65	68.60	88.55	99.25	47.00	69.25	82.25	94.55	99.85
	$S_{n,T}^{(3)}$	10	2.90	2.60	2.90	4.45	7.25	9.70	10.00	10.15	13.40	19.80
		20	3.95	3.70	4.25	5.80	12.80	11.20	11.85	13.95	18.00	29.20
		30	4.20	4.35	5.95	7.75	17.70	12.40	13.90	16.85	22.10	37.80
		50	7.55	7.75	9.15	16.15	34.60	17.70	19.45	24.15	35.25	57.95
		100	12.30	18.65	26.65	45.35	78.30	24.90	35.50	47.20	66.80	90.95
		200	19.55	32.00	44.40	69.85	96.00	35.75	52.45	68.35	87.65	99.10
Fixed	$S_{n,T}^{(4)}$	10	0.05	0.60	1.00	2.40	5.95	3.20	5.60	7.80	11.20	17.95
		20	0.15	1.05	1.85	3.40	9.50	4.75	7.75	10.20	15.00	26.95
		30	0.50	1.25	2.75	5.55	14.00	5.90	10.30	13.40	19.40	35.00
		50	2.00	4.15	6.30	13.40	30.30	10.80	17.60	22.65	33.15	55.80
		100	10.70	27.35	38.85	59.50	87.10	26.90	46.90	59.80	77.85	94.90
		200	16.75	42.00	59.65	83.80	98.65	39.35	65.30	79.25	94.05	99.90
Expanding	$S_{n,T}^{(4)}$	10	0.45	0.75	1.05	2.35	5.35	4.15	5.70	7.80	10.85	17.25
		20	0.15	1.05	1.85	3.40	9.50	4.75	7.75	10.20	15.00	26.95
		30	0.50	1.25	2.75	5.55	14.00	5.90	10.30	13.40	19.40	35.00
		50	2.00	4.15	6.30	13.40	30.30	10.80	17.60	22.65	33.15	55.80
		100	5.75	17.95	30.15	51.50	84.00	20.60	40.30	53.30	73.25	93.90
		200	9.70	34.10	50.40	77.90	97.60	32.75	58.40	74.30	91.65	99.60
Fixed	$S_{n,T}^{(5)}$	10	0.05	0.60	0.95	2.40	5.90	3.05	5.55	7.65	11.10	17.80
		20	0.10	0.85	1.75	3.05	8.85	4.05	7.15	9.40	14.00	26.30
		30	0.10	0.75	2.10	4.30	12.25	4.10	7.95	11.45	16.75	31.55
		50	0.45	1.85	3.65	8.35	22.75	7.50	12.70	17.35	27.40	49.45
		100	2.75	8.45	17.20	34.95	70.60	14.10	29.80	41.60	61.70	88.30
		200	4.30	17.65	32.70	60.40	93.05	22.60	45.25	63.15	85.10	98.90
Expanding	$S_{n,T}^{(5)}$	10	0.20	0.65	0.90	2.20	4.45	3.25	5.00	7.05	9.85	16.15
		20	0.10	0.90	1.75	3.10	9.00	4.15	7.30	9.65	14.10	26.50
		30	0.20	0.85	2.15	4.50	12.55	4.60	8.25	11.90	17.25	32.20
		50	0.55	2.35	4.05	9.40	23.95	8.35	13.30	18.00	28.55	50.10
		100	2.25	9.00	18.20	36.90	72.15	15.30	29.95	42.35	62.95	89.15
		200	3.70	18.60	34.05	62.00	93.85	23.80	46.45	63.50	85.10	98.85

Joint EPA Test

Option	Test	$n\backslash T$	1% Nominal Size 10	20	30	50	100	5% Nominal Size 10	20	30	50	100
	$J_{n,T}^{(1)}$	10	17.50	16.00	16.85	20.60	27.05	25.75	22.55	24.40	28.85	35.65
		20	21.85	20.80	22.75	26.50	39.40	31.75	28.65	30.25	35.25	47.30
		30	26.75	21.30	24.35	30.00	45.15	38.90	31.20	31.45	39.15	53.95
		50	35.05	28.25	30.45	37.95	57.35	47.85	37.70	41.10	48.85	67.35
		100	51.00	39.55	43.05	52.80	79.30	63.10	50.90	55.20	63.10	85.55
		200	73.35	56.70	58.40	72.80	92.95	83.65	69.35	70.10	81.15	96.35
Truncated	$J_{n,T}^{(2)}$	10	2.25	0.75	0.70	1.45	2.20	4.10	2.00	2.00	3.25	5.45
		20	8.80	5.35	4.90	3.65	2.60	11.70	7.40	6.50	4.90	4.20
		30	10.65	9.90	9.45	8.55	8.00	13.20	12.00	11.35	11.40	10.85
		50	14.45	12.00	11.80	10.95	10.75	16.70	14.25	14.05	12.50	12.60
		100	19.20	17.60	20.85	20.10	22.70	21.45	19.15	22.70	22.70	26.30
		200	20.15	22.25	23.10	26.50	31.35	21.45	23.65	25.10	29.00	33.85
Bartlett	$J_{n,T}^{(2)}$	10	17.50	16.00	16.85	20.60	27.05	25.75	22.55	24.40	28.85	35.65
		20	4.75	2.90	2.55	3.50	8.35	9.25	5.95	6.25	7.90	15.00
		30	5.55	2.25	2.40	3.35	7.75	10.60	5.70	5.25	6.80	15.20
		50	7.00	1.70	1.80	3.25	10.15	14.50	5.20	4.95	7.60	17.15
		100	2.35	0.00	0.05	0.00	0.45	6.40	0.20	0.10	0.20	2.10
		200	27.55	0.40	0.15	0.20	1.25	43.70	1.75	0.85	0.70	4.15
Parzen	$J_{n,T}^{(2)}$	10	17.50	16.00	16.85	20.60	27.05	25.75	22.55	24.40	28.85	35.65
		20	9.05	7.80	8.60	10.75	20.30	15.15	13.60	14.30	17.30	29.35
		30	9.40	7.25	7.70	10.40	21.05	17.50	11.95	14.05	17.50	30.50
		50	12.10	8.15	8.75	13.65	27.00	22.50	15.00	14.90	21.50	37.45
		100	2.35	0.10	0.15	0.30	3.95	6.30	1.00	0.75	1.75	9.20
		200	12.35	0.55	0.40	1.05	8.80	25.20	2.10	1.60	3.20	16.90
Tukey	$J_{n,T}^{(2)}$	10	17.50	16.00	16.85	20.60	27.05	25.75	22.55	24.40	28.85	35.65
		20	6.40	3.40	3.00	4.40	9.70	11.75	7.25	7.10	9.15	17.05
		30	6.55	3.15	2.85	3.85	9.10	12.70	6.85	6.20	7.70	17.30
		50	8.30	2.40	2.50	3.90	12.05	17.20	6.30	6.30	9.30	19.45
		100	22.90	0.90	0.20	0.20	1.70	38.35	3.05	1.25	1.45	5.65
		200	88.10	6.95	1.80	1.35	5.80	94.25	17.70	5.75	4.90	13.70
QS	$J_{n,T}^{(2)}$	10	11.85	11.25	11.70	14.90	21.20	19.45	17.95	18.55	22.85	29.15
		20	7.30	2.30	2.00	2.25	5.95	14.10	5.75	5.00	6.55	11.80
		30	10.20	2.35	1.95	2.20	4.85	21.05	6.60	5.30	5.65	11.45
		50	20.50	3.10	1.30	2.55	6.40	35.25	7.55	5.70	5.95	13.70
		100	67.05	4.20	1.05	0.40	1.70	83.20	12.95	4.20	2.65	5.80
		200	100.00	59.45	17.35	5.60	7.90	100.00	80.30	36.00	16.50	19.85
	$J_{n,T}^{(3)}$	10		39.65	19.35	9.20	5.25		56.50	35.50	22.15	14.35
		20			84.05	39.80	14.05			92.40	57.90	30.80
		30				87.40	35.30				93.55	54.75
		50					90.90					95.85
		100										
		200										
Fixed	$J_{n,T}^{(4)}$	10	2.40	2.70	3.70	4.55	5.95	8.90	10.90	11.20	13.50	15.90
		20	3.20	4.00	5.05	5.85	8.90	10.05	10.10	12.30	12.40	17.65
		30	3.35	5.05	6.35	6.30	9.50	9.90	12.45	13.55	13.55	17.90
		50	5.10	5.45	7.20	7.75	9.85	12.50	12.00	13.35	14.95	18.65
		100	9.85	10.45	14.65	20.55	35.40	17.45	18.65	23.95	29.40	46.65
		200	11.90	11.15	13.45	22.40	39.20	19.55	19.60	21.05	31.90	48.30
Expanding	$J_{n,T}^{(4)}$	10	4.05	4.95	6.30	6.90	8.25	10.60	11.80	12.95	12.80	16.30
		20	3.20	4.00	5.05	5.85	8.90	10.05	10.10	12.30	12.40	17.65
		30	3.35	5.05	6.35	6.30	9.50	9.90	12.45	13.55	13.55	17.90
		50	5.10	5.45	7.20	7.75	9.85	12.50	12.00	13.35	14.95	18.65
		100	10.50	9.10	12.55	15.70	26.65	18.50	17.20	21.00	25.40	37.55
		200	13.50	11.10	9.40	13.50	24.85	20.20	18.90	16.55	22.20	35.25
Fixed	$J_{n,T}^{(5)}$	10	5.90	7.40	5.40	4.25	4.60	10.45	14.85	12.45	12.90	15.35
		20	5.45	7.75	8.15	6.80	4.65	7.00	10.35	11.40	11.20	9.35
		30	4.90	7.40	10.15	11.10	11.65	6.00	9.80	13.70	14.35	17.45
		50	5.55	9.05	11.70	13.75	18.70	6.50	11.15	14.10	17.25	23.75
		100	5.20	9.75	12.80	16.15	23.40	6.25	11.35	14.75	19.65	27.30
		200	3.95	8.60	12.55	15.90	25.50	4.30	9.70	13.75	17.60	28.25
Expanding	$J_{n,T}^{(5)}$	10	2.80	3.20	2.20	2.45	2.05	5.05	5.50	4.80	4.65	4.65
		20	5.85	9.65	9.10	9.05	6.80	7.85	12.80	14.10	14.45	13.70
		30	5.75	10.35	12.10	12.90	14.20	7.40	13.25	17.15	18.00	20.30
		50	7.60	12.35	15.10	17.10	22.40	9.15	14.85	18.90	21.20	29.65
		100	6.45	13.00	16.20	22.65	28.45	7.55	15.50	18.30	26.55	33.60
		200	3.95	10.60	15.75	22.10	31.95	4.50	11.45	17.35	24.35	35.25

Table B8: Power Under Homogeneous Alternative – DGP 2: Factor Dependence, No Spatial Dependence

			Overall EPA Test												Joint EPA Test										
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	94.15	99.40	100.00	100.00	100.00	96.45	99.60	100.00	100.00	100.00	$J_{n,T}^{(1)}$	10	91.20	98.85	100.00	100.00	100.00	93.90	99.25	100.00	100.00	100.00
		20	97.65	99.95	100.00	100.00	100.00	98.60	100.00	100.00	100.00	100.00		20	95.20	99.85	100.00	100.00	100.00	96.50	99.90	100.00	100.00	100.00
		30	97.95	99.90	100.00	100.00	100.00	98.90	99.95	100.00	100.00	100.00		30	96.50	99.80	100.00	100.00	100.00	97.60	99.90	100.00	100.00	100.00
		50	98.35	99.90	100.00	100.00	100.00	98.65	99.95	100.00	100.00	100.00		50	97.65	99.95	100.00	100.00	100.00	98.35	100.00	100.00	100.00	100.00
		100	99.20	99.95	100.00	100.00	100.00	99.45	99.95	100.00	100.00	100.00		100	98.55	100.00	100.00	100.00	100.00	98.95	100.00	100.00	100.00	100.00
		200	99.40	100.00	100.00	100.00	100.00	99.60	100.00	100.00	100.00	100.00		200	99.15	100.00	100.00	100.00	100.00	99.45	100.00	100.00	100.00	100.00
Truncated	$S_{n,T}^{(2)}$	10	85.40	97.90	99.55	100.00	100.00	92.05	98.90	99.95	100.00	100.00	$J_{n,T}^{(2)}$	10	64.75	85.90	94.90	96.85	98.10	72.90	90.15	96.05	96.95	98.10
		20	83.40	97.80	99.60	100.00	100.00	91.50	99.15	99.95	100.00	100.00		20	53.10	71.50	81.50	87.50	91.70	57.95	75.05	83.80	88.20	91.90
		30	89.30	98.75	99.95	100.00	100.00	94.20	99.55	100.00	100.00	100.00		30	50.90	66.85	75.35	82.55	86.70	54.50	70.25	77.15	83.00	86.95
		50	94.00	99.30	99.95	100.00	100.00	96.35	99.65	99.95	100.00	100.00		50	54.55	68.90	76.30	82.00	85.65	57.85	71.50	77.20	82.70	85.85
		100	96.20	99.75	99.95	100.00	100.00	97.40	99.95	99.95	100.00	100.00		100	58.95	73.25	80.45	84.40	86.00	61.00	74.80	80.90	85.00	86.00
		200	96.55	99.85	100.00	100.00	100.00	98.05	99.95	100.00	100.00	100.00		200	46.25	61.40	70.15	75.05	79.15	47.35	62.70	70.65	75.55	79.40
Bartlett	$S_{n,T}^{(2)}$	10	94.15	99.40	100.00	100.00	100.00	96.45	99.60	100.00	100.00	100.00	$J_{n,T}^{(2)}$	10	91.20	98.85	100.00	100.00	100.00	93.90	99.25	100.00	100.00	100.00
		20	94.20	99.55	100.00	100.00	100.00	96.75	99.85	100.00	100.00	100.00		20	91.80	99.30	100.00	100.00	100.00	95.45	99.80	100.00	100.00	100.00
		30	96.05	99.80	100.00	100.00	100.00	97.45	99.90	100.00	100.00	100.00		30	95.35	99.70	100.00	100.00	100.00	97.40	99.85	100.00	100.00	100.00
		50	97.30	99.80	99.95	100.00	100.00	98.00	99.90	100.00	100.00	100.00		50	98.00	100.00	100.00	100.00	100.00	98.85	100.00	100.00	100.00	100.00
		100	97.80	99.95	99.95	100.00	100.00	98.65	99.95	99.95	100.00	100.00		100	99.90	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
		200	98.55	100.00	100.00	100.00	100.00	99.10	100.00	100.00	100.00	100.00		200	99.30	100.00	100.00	100.00	100.00	99.35	100.00	100.00	100.00	100.00
Parzen	$S_{n,T}^{(2)}$	10	94.15	99.40	100.00	100.00	100.00	96.45	99.60	100.00	100.00	100.00	$J_{n,T}^{(2)}$	10	91.20	98.85	100.00	100.00	100.00	93.90	99.25	100.00	100.00	100.00
		20	96.30	99.80	100.00	100.00	100.00	98.10	99.95	100.00	100.00	100.00		20	92.15	99.40	100.00	100.00	100.00	95.20	99.80	100.00	100.00	100.00
		30	97.15	99.90	100.00	100.00	100.00	98.00	99.90	100.00	100.00	100.00		30	94.85	99.80	100.00	100.00	100.00	96.50	99.80	100.00	100.00	100.00
		50	97.85	99.85	100.00	100.00	100.00	98.45	99.90	100.00	100.00	100.00		50	96.65	100.00	100.00	100.00	100.00	98.00	100.00	100.00	100.00	100.00
		100	98.55	99.95	99.95	100.00	100.00	98.90	99.95	100.00	100.00	100.00		100	99.35	100.00	100.00	100.00	100.00	99.70	100.00	100.00	100.00	100.00
		200	99.00	100.00	100.00	100.00	100.00	99.35	100.00	100.00	100.00	100.00		200	99.85	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Tukey	$S_{n,T}^{(2)}$	10	94.15	99.40	100.00	100.00	100.00	96.45	99.60	100.00	100.00	100.00	$J_{n,T}^{(2)}$	10	91.20	98.85	100.00	100.00	100.00	93.90	99.25	100.00	100.00	100.00
		20	94.60	99.55	100.00	100.00	100.00	96.75	99.85	100.00	100.00	100.00		20	93.05	99.30	100.00	100.00	100.00	96.15	99.80	100.00	100.00	100.00
		30	96.25	99.80	100.00	100.00	100.00	97.65	99.90	100.00	100.00	100.00		30	96.50	99.75	100.00	100.00	100.00	97.50	99.85	100.00	100.00	100.00
		50	97.35	99.85	100.00	100.00	100.00	98.05	99.90	100.00	100.00	100.00		50	98.30	100.00	100.00	100.00	100.00	99.05	100.00	100.00	100.00	100.00
		100	97.85	99.95	99.95	100.00	100.00	98.65	99.95	99.95	100.00	100.00		100	99.75	100.00	100.00	100.00	100.00	99.75	100.00	100.00	100.00	100.00
		200	98.65	100.00	100.00	100.00	100.00	99.25	100.00	100.00	100.00	100.00		200	96.50	100.00	100.00	100.00	100.00	96.60	100.00	100.00	100.00	100.00
QS	$S_{n,T}^{(2)}$	10	93.35	99.20	100.00	100.00	100.00	96.10	99.60	100.00	100.00	100.00	$J_{n,T}^{(2)}$	10	89.55	98.65	99.90	100.00	100.00	93.05	99.10	100.00	100.00	100.00
		20	92.40	99.30	100.00	100.00	100.00	95.80	99.75	100.00	100.00	100.00		20	96.10	99.65	100.00	100.00	100.00	97.80	99.85	100.00	100.00	100.00
		30	95.10	99.65	100.00	100.00	100.00	97.05	99.85	100.00	100.00	100.00		30	98.70	99.85	100.00	100.00	100.00	99.35	100.00	100.00	100.00	100.00
		50	96.95	99.70	99.95	100.00	100.00	97.75	99.85	100.00	100.00	100.00		50	99.95	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
		100	97.30	99.90	99.95	100.00	100.00	98.55	99.95	99.95	100.00	100.00		100	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
		200	98.15	99.95	100.00	100.00	100.00	98.80	100.00	100.00	100.00	100.00		200	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
	$S_{n,T}^{(3)}$	10	59.70	87.10	96.55	99.80	100.00	78.35	95.60	99.30	99.95	100.00	$J_{n,T}^{(3)}$	10		98.45	99.85	99.95	100.00		99.75	100.00	100.00	100.00
		20	60.65	88.20	97.65	100.00	100.00	78.00	96.45	99.35	100.00	100.00		20			99.95	100.00	100.00			99.95	100.00	100.00
		30	60.60	87.65	97.80	100.00	100.00	77.60	95.75	99.60	100.00	100.00		30				100.00	100.00				100.00	100.00
		50	60.65	88.25	97.85	100.00	100.00	78.90	96.30	99.50	100.00	100.00		50					100.00					100.00
		100	60.65	88.10	97.30	100.00	100.00	79.00	96.15	99.35	100.00	100.00		100										
		200	61.00	89.85	98.35	99.95	100.00	77.85	96.95	99.75	100.00	100.00		200										
Fixed	$S_{n,T}^{(4)}$	10	14.05	70.30	93.10	99.60	100.00	60.90	92.75	98.80	99.95	100.00	$J_{n,T}^{(4)}$	10	1.05	13.80	70.10	99.30	100.00	4.55	50.45	96.05	99.90	100.00
		20	15.50	73.60	94.40	99.85	100.00	62.80	94.05	98.90	100.00	100.00		20	1.85	14.40	58.40	99.65	100.00	5.50	34.00	84.25	100.00	100.00
		30	13.95	73.40	94.90	99.95	100.00	62.10	93.70	99.15	100.00	100.00		30	3.00	19.90	58.55	98.70	100.00	6.85	34.70	78.80	99.85	100.00
		50	15.30	74.25	95.25	100.00	100.00	63.05	94.35	99.25	100.00	100.00		50	4.55	25.05	62.50	97.90	100.00	8.70	36.50	76.50	99.10	100.00
		100	15.95	75.05	94.95	99.85	100.00	62.60	93.85	99.10	100.00	100.00		100	7.10	33.80	68.10	98.00	100.00	9.80	42.45	76.35	99.05	100.00
		200	14.90	77.25	96.35	99.85	100.00	62.95	94.90	99.55	100.00	100.00		200	10.70	39.30	71.55	98.60	100.00	12.95	45.00	76.80	99.40	100.00
Expanding	$S_{n,T}^{(4)}$	10	13.40	69.95	92.80	99.60	100.00	60.10	92.70	98.70	99.95	100.00	$J_{n,T}^{(4)}$	10	2.75	25.30	73.55	98.85	100.00	11.45	60.50	95.60	99.95	100.00
		20	15.50	73.60	94.40	99.85	100.00	62.80	94.05	98.90	100.00	100.00		20	1.85	14.40	58.40	99.65	100.00	5.50	34.00	84.25	100.00	100.00
		30	13.95	73.40	94.90	99.95	100.00	62.10	93.70	99.15	100.00	100.00		30	3.00	19.90	58.55	98.70	100.00	6.85	34.70	78.80	99.85	100.00
		50	15.30	74.25	95.25	100.00	100.00	63.05	94.35	99.25	100.00	100.00		50	4.55	25.05	62.50	97.90	100.00	8.70	36.50	76.50	99.10	100.00
		100	15.95	75.05	94.95	99.85	100.00	62.60	93.85	99.10	100.00	100.00		100	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		200	14.90	77.20	96.30	99.85	100.00	62.95	94.85	99.55	100.00	100.00		200	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fixed	$S_{n,T}^{(5)}$	10	14.30	70.60	93.30	99.60	100.00	61.20	92.80	98.80	99.95	100.00	$J_{n,T}^{(5)}$	10	2.15	7.60	65.15	99.05	100.00	5.20	45.50	95.95	99.85	100.00
		20	15.65	73.85	94.45	99.85	100.00	63.05	94.20	98.90	100.00	100.00		20	3.45	8.00	26.40	99.15	100.00	4.60	15.35	69.45	100.00	100.00
		30	14.00	73.55	94.90	99.95	100.00	62.15	93.75	99.25	100.00	100.00		30	2.80	7.90	25.00	96.40	100.00	3.80	13.15	51.05	99.85	100.00
		50	15.40	74.30	95.25	100.00	100.00	63.05	94.35	99.25	100.00	100.00		50	3.35	7.95	24.55	91.40	100.00	4.00	12.30	41.25	97.60	100.00
		100	15.90	75.10	95.00	99.85	100.00	62.60	93.85	99.10	100.00	100.00		100	2.30	8.75	22.95	83.70	99.95	2.70	11.30	33.15	92.15	100.00
		200	14.90	77.25	96.35	99.85	100.00	62.95	94.95	99.55	100.00	100.00		200	1.15	4.55	10.50	52.25	99.90	1.25	5.15	12.05	62.15	99.90
Expanding	$S_{n,T}^{(5)}$	10	14.05	70.40	93.15	99.60	100.00	60.85	92.80	98.80	99.95	100.00	$J_{n,T}^{(5)}$	10	24.30	51.70	84.05	98.70	100.00	37.30	77.45	96.45	99.55	100.00
		20	15.65	73.95	94.45	99.85	100.00	63.10	94.25	98.90	100.00	100.00		20	16.45	44.85	83.40	99.85	100.00	20.75	58.10	94.95	100.00	100.00
		30	14.00	73.60	94.90	99.95	100.00	62.30	93.75	99.25	100.00	100.00		30	14.55	44.75	82.70	99.60	100.00	17.70	53.40	88.80	99.90	100.00
		50	15.45	74.35	95.25	100.00	100.00	63.15	94.45	99.25	100.00	100.00		50	15.30	41.40	78.80	99.45	100.00	17.90	46.70	83.00	99.55	100.00
		100	15.95	75.10	95.00	99.85	100.00	62.65	93.85	99.10	100.00	100.00		100	4.60	4.40	2.15	0.00	0.00	5.05	4.80	2.60	0.00	0.00
		200	14.90	77.20	96.30	99.85	100.00	62.95	94.85	99.55	100.00	100.00		200	1.70	1.20	1.55	0.45	0.00	1.75	1.35	1.70	0.55	0.00

Table B9: Power Under Homogeneous Alternative – DGP 2: Factor Dependence, Low Spatial Dependence

			Overall EPA Test												Joint EPA Test										
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n \backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n \backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	93.35	99.25	99.90	100.00	100.00	95.30	99.60	100.00	100.00	100.00	$J_{n,T}^{(1)}$	10	88.90	98.05	99.80	100.00	100.00	92.05	99.15	99.90	100.00	100.00
		20	96.90	99.70	100.00	100.00	100.00	97.95	99.80	100.00	100.00	100.00		20	93.80	99.40	100.00	100.00	100.00	95.65	99.60	100.00	100.00	100.00
		30	98.10	99.80	100.00	100.00	100.00	98.70	99.95	100.00	100.00	100.00		30	95.80	99.60	100.00	100.00	100.00	97.20	99.75	100.00	100.00	100.00
		50	98.45	100.00	100.00	100.00	100.00	99.05	100.00	100.00	100.00	100.00		50	97.65	99.95	100.00	100.00	100.00	98.40	100.00	100.00	100.00	100.00
		100	99.30	100.00	100.00	100.00	100.00	99.50	100.00	100.00	100.00	100.00		100	98.90	99.95	100.00	100.00	100.00	99.25	100.00	100.00	100.00	100.00
		200	99.60	100.00	100.00	100.00	100.00	99.70	100.00	100.00	100.00	100.00		200	99.30	100.00	100.00	100.00	100.00	99.40	100.00	100.00	100.00	100.00
Truncated	$S_{n,T}^{(2)}$	10	81.45	96.10	99.60	99.95	100.00	89.95	98.25	99.85	100.00	100.00	$J_{n,T}^{(2)}$	10	64.60	86.70	96.45	99.65	99.95	74.95	91.70	98.10	99.90	99.95
		20	79.40	96.60	99.70	100.00	100.00	88.95	98.65	99.85	100.00	100.00		20	47.30	66.70	75.75	83.40	88.35	52.55	70.70	78.75	84.30	88.60
		30	87.00	98.55	99.75	100.00	100.00	93.45	99.40	100.00	100.00	100.00		30	49.10	65.15	72.40	79.45	84.90	53.10	68.30	74.60	80.75	85.20
		50	92.50	99.45	99.95	100.00	100.00	95.80	99.80	100.00	100.00	100.00		50	49.30	67.80	77.40	84.05	87.30	53.40	70.65	79.45	84.85	87.45
		100	96.30	99.85	100.00	100.00	100.00	98.25	99.90	100.00	100.00	100.00		100	55.65	73.20	78.60	83.95	87.45	57.85	74.90	79.75	84.45	87.55
		200	96.80	99.75	100.00	100.00	100.00	98.30	99.85	100.00	100.00	100.00		200	45.55	60.40	67.60	76.10	79.95	46.70	61.85	68.65	76.45	80.20
Bartlett	$S_{n,T}^{(2)}$	10	93.35	99.25	99.90	100.00	100.00	95.30	99.60	100.00	100.00	100.00	$J_{n,T}^{(2)}$	10	88.90	98.05	99.80	100.00	100.00	92.05	99.15	99.90	100.00	100.00
		20	92.30	99.20	99.95	100.00	100.00	95.90	99.45	100.00	100.00	100.00		20	88.40	98.75	100.00	100.00	100.00	92.90	99.50	100.00	100.00	100.00
		30	95.45	99.55	100.00	100.00	100.00	97.20	99.70	100.00	100.00	100.00		30	93.40	99.65	99.95	100.00	100.00	95.95	99.80	100.00	100.00	100.00
		50	97.10	99.85	100.00	100.00	100.00	98.00	99.95	100.00	100.00	100.00		50	97.50	99.95	100.00	100.00	100.00	98.70	100.00	100.00	100.00	100.00
		100	98.45	99.90	100.00	100.00	100.00	98.90	100.00	100.00	100.00	100.00		100	99.75	100.00	100.00	100.00	100.00	99.85	100.00	100.00	100.00	100.00
		200	98.80	99.95	100.00	100.00	100.00	99.15	100.00	100.00	100.00	100.00		200	99.45	100.00	100.00	100.00	100.00	99.45	100.00	100.00	100.00	100.00
Parzen	$S_{n,T}^{(2)}$	10	93.35	99.25	99.90	100.00	100.00	95.30	99.60	100.00	100.00	100.00	$J_{n,T}^{(2)}$	10	88.90	98.05	99.80	100.00	100.00	92.05	99.15	99.90	100.00	100.00
		20	95.25	99.45	100.00	100.00	100.00	97.10	99.75	100.00	100.00	100.00		20	89.40	98.95	100.00	100.00	100.00	92.85	99.35	100.00	100.00	100.00
		30	97.00	99.70	100.00	100.00	100.00	98.15	99.80	100.00	100.00	100.00		30	93.05	99.50	99.95	100.00	100.00	95.20	99.65	100.00	100.00	100.00
		50	97.90	99.95	100.00	100.00	100.00	98.55	100.00	100.00	100.00	100.00		50	96.35	99.85	100.00	100.00	100.00	97.45	100.00	100.00	100.00	100.00
		100	98.55	100.00	100.00	100.00	100.00	99.15	100.00	100.00	100.00	100.00		100	99.10	100.00	100.00	100.00	100.00	99.65	100.00	100.00	100.00	100.00
		200	99.10	100.00	100.00	100.00	100.00	99.40	100.00	100.00	100.00	100.00		200	99.95	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Tukey	$S_{n,T}^{(2)}$	10	93.35	99.25	99.90	100.00	100.00	95.30	99.60	100.00	100.00	100.00	$J_{n,T}^{(2)}$	10	88.90	98.05	99.80	100.00	100.00	92.05	99.15	99.90	100.00	100.00
		20	92.65	99.25	99.95	100.00	100.00	96.05	99.45	100.00	100.00	100.00		20	90.25	99.10	100.00	100.00	100.00	93.80	99.65	100.00	100.00	100.00
		30	95.60	99.60	100.00	100.00	100.00	97.35	99.70	100.00	100.00	100.00		30	93.95	99.65	100.00	100.00	100.00	96.15	99.80	100.00	100.00	100.00
		50	97.25	99.85	100.00	100.00	100.00	98.05	99.95	100.00	100.00	100.00		50	96.70	99.75	99.95	100.00	100.00	97.50	99.80	99.95	100.00	100.00
		100	98.45	99.90	100.00	100.00	100.00	98.95	100.00	100.00	100.00	100.00		100	97.70	99.90	100.00	100.00	100.00	97.85	99.90	100.00	100.00	100.00
		200	98.85	99.95	100.00	100.00	100.00	99.15	100.00	100.00	100.00	100.00		200	94.40	99.60	100.00	100.00	100.00	94.45	99.60	100.00	100.00	100.00
QS	$S_{n,T}^{(2)}$	10	92.35	99.05	99.85	100.00	100.00	94.75	99.55	100.00	100.00	100.00	$J_{n,T}^{(2)}$	10	86.75	97.55	99.80	100.00	100.00	90.65	98.75	99.85	100.00	100.00
		20	90.55	98.90	99.90	100.00	100.00	94.70	99.35	100.00	100.00	100.00		20	94.25	99.55	100.00	100.00	100.00	96.70	99.95	100.00	100.00	100.00
		30	94.40	99.45	100.00	100.00	100.00	96.55	99.70	100.00	100.00	100.00		30	97.80	100.00	100.00	100.00	100.00	99.00	100.00	100.00	100.00	100.00
		50	96.35	99.85	100.00	100.00	100.00	97.70	99.90	100.00	100.00	100.00		50	99.80	100.00	100.00	100.00	100.00	99.80	100.00	100.00	100.00	100.00
		100	98.05	99.90	100.00	100.00	100.00	98.50	99.95	100.00	100.00	100.00		100	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
		200	98.35	99.90	100.00	100.00	100.00	98.95	100.00	100.00	100.00	100.00		200	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
	$S_{n,T}^{(3)}$	10	55.05	83.00	95.25	99.70	100.00	74.25	93.05	98.95	99.95	100.00	$J_{n,T}^{(3)}$	10		99.30	99.60	100.00	100.00		99.65	99.85	100.00	100.00
		20	55.00	84.20	96.15	99.70	100.00	74.95	94.80	99.35	100.00	100.00		20			100.00	100.00	100.00			100.00	100.00	100.00
		30	58.05	88.55	96.75	99.85	100.00	77.65	95.60	99.25	100.00	100.00		30				100.00	100.00				100.00	100.00
		50	59.25	88.35	97.80	99.80	100.00	78.15	95.40	99.45	99.95	100.00		50					100.00					100.00
		100	59.40	88.35	97.55	99.95	100.00	78.95	96.60	99.65	100.00	100.00		100										
		200	58.15	88.40	97.85	99.95	100.00	77.25	96.30	99.65	100.00	100.00		200										
Fixed	$S_{n,T}^{(4)}$	10	12.95	66.25	90.40	99.50	100.00	56.95	89.75	98.40	99.95	100.00	$J_{n,T}^{(4)}$	10	1.50	21.10	75.35	99.35	100.00	7.80	59.75	96.30	99.95	100.00
		20	13.20	68.55	92.15	99.50	100.00	56.90	91.45	98.75	100.00	100.00		20	2.30	19.20	58.85	99.65	100.00	7.40	38.20	84.90	100.00	100.00
		30	13.70	73.60	93.65	99.75	100.00	59.90	93.50	99.00	100.00	100.00		30	3.30	20.70	57.45	99.10	100.00	7.65	36.45	77.65	100.00	100.00
		50	14.80	73.65	94.75	99.65	100.00	61.70	93.35	99.25	99.95	100.00		50	5.40	25.55	63.70	98.00	100.00	10.30	37.60	76.65	99.05	100.00
		100	15.00	74.15	94.35	99.90	100.00	61.80	94.75	99.25	100.00	100.00		100	7.20	33.20	69.75	97.70	100.00	11.40	41.45	77.90	98.75	100.00
		200	14.30	75.20	95.55	99.95	100.00	60.25	94.65	99.35	100.00	100.00		200	11.75	39.50	76.30	98.70	100.00	14.50	45.95	81.50	99.35	100.00
Expanding	$S_{n,T}^{(4)}$	10	12.05	65.35	90.25	99.45	100.00	56.10	89.60	98.35	99.95	100.00	$J_{n,T}^{(4)}$	10	3.95	26.90	74.05	99.20	100.00	13.95	60.35	94.35	99.85	100.00
		20	13.20	68.55	92.15	99.50	100.00	56.90	91.45	98.75	100.00	100.00		20	2.30	19.20	58.85	99.65	100.00	7.40	38.20	84.90	100.00	100.00
		30	13.70	73.60	93.65	99.75	100.00	59.90	93.50	99.00	100.00	100.00		30	3.30	20.70	57.45	99.10	100.00	7.65	36.45	77.65	100.00	100.00
		50	14.80	73.65	94.75	99.65	100.00	61.70	93.35	99.25	99.95	100.00		50	5.40	25.55	63.70	98.00	100.00	10.30	37.60	76.65	99.05	100.00
		100	15.00	74.10	94.35	99.90	100.00	61.75	94.70	99.25	100.00	100.00		100	0.10	0.00	0.05	0.05	0.10	0.20	0.20	0.05	0.05	0.95
		200	14.35	75.20	95.50	99.95	100.00	60.25	94.60	99.35	100.00	100.00		200	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fixed	$S_{n,T}^{(5)}$	10	12.70	66.10	90.35	99.50	100.00	57.00	89.75	98.40	99.95	100.00	$J_{n,T}^{(5)}$	10	3.45	13.60	69.90	99.20	100.00	7.90	53.00	95.85	99.95	100.00
		20	13.05	68.20	92.10	99.50	100.00	56.55	91.45	98.70	100.00	100.00		20	3.55	9.60	31.75	92.45	98.70	4.65	17.85	63.20	94.10	98.75
		30	13.45	73.25	93.50	99.75	100.00	59.60	93.35	99.00	100.00	100.00		30	3.65	9.00	26.55	91.90	99.70	4.45	14.80	48.70	94.90	99.70
		50	14.20	73.30	94.70	99.60	100.00	61.10	93.25	99.20	99.95	100.00		50	3.80	9.40	28.15	88.40	99.75	4.80	12.75	43.60	92.45	99.75
		100	15.00	73.80	94.35	99.90	100.00	61.55	94.45	99.25	100.00	100.00		100	2.80	8.40	27.45	86.05	99.65	2.95	11.05	35.20	90.65	99.70
		200	14.25	75.15	95.45	99.95	100.00	60.15	94.55	99.35	100.00	100.00		200	2.15	4.60	12.25	52.15	96.75	2.25	5.15	15.35	59.20	96.80
Expanding	$S_{n,T}^{(5)}$	10	11.80	64.95	90.05	99.45	100.00	55.95	89.55	98.35	99.95	100.00	$J_{n,T}^{(5)}$	10	25.45	52.10	84.40	98.50	99.70	36.40	75.25	94.95	99.05	99.70
		20	13.05	68.40	92.15	99.50	100.00	56.70	91.45	98.75	100.00	100.00		20	18.40	42.00	68.20	90.05	97.95	21.95	52.35	77.75	91.05	98.10
		30	13.50	73.30	93.60	99.75	100.00	59.80	93.35	99.00	100.00	100.00		30	14.65	42.20	66.40	92.15	99.45	17.80	50.80	73.00	92.65	99.50
		50	14.30	73.35	94.70	99.60	100.00	61.30	93.25	99.20	99.95	100.00		50	16.70	39.40	66.60	92.95	100.00	19.10	44.00	70.50	93.90	100.00
		100	15.00	74.00	94.35	99.90	100.00	61.70	94.60	99.25	100.00	100.00		100	5.35	7.95	7.40	3.20	1.90	5.70	9.30	8.50	3.90	6.55
		200	14.30	75.10	95.45	99.95	100.00	60.20	94.55	99.35	100.00	100.00		200	2.15	2.50	2.00	1.05	0.00	2.25	2.55	2.05	1.40	0.00

Table B10: Power Under Homogeneous Alternative – DGP 2: Factor Dependence, High Spatial Dependence

			Overall EPA Test												Joint EPA Test									
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	91.80	98.50	99.85	100.00	100.00	94.55	99.10	99.85	100.00	100.00	$J_{n,T}^{(1)}$	10	83.55	96.20	99.70	100.00	100.00	87.70	97.75	99.80	100.00	100.00
		20	95.20	99.25	99.95	100.00	100.00	97.05	99.45	100.00	100.00	100.00		20	88.00	98.45	99.90	100.00	100.00	90.85	98.70	99.95	100.00	100.00
		30	97.45	99.75	100.00	100.00	100.00	98.35	99.75	100.00	100.00	100.00		30	92.65	99.15	99.95	100.00	100.00	94.05	99.25	100.00	100.00	100.00
		50	97.90	99.90	100.00	100.00	100.00	98.40	99.90	100.00	100.00	100.00		50	95.60	99.90	100.00	100.00	100.00	96.60	99.90	100.00	100.00	100.00
		100	99.25	100.00	100.00	100.00	100.00	99.35	100.00	100.00	100.00	100.00		100	98.15	100.00	100.00	100.00	100.00	98.75	100.00	100.00	100.00	100.00
		200	99.55	100.00	100.00	100.00	100.00	99.70	100.00	100.00	100.00	100.00		200	99.00	100.00	100.00	100.00	100.00	99.30	100.00	100.00	100.00	100.00
Truncated	$S_{n,T}^{(2)}$	10	77.05	93.60	99.05	99.95	100.00	86.35	96.75	99.75	100.00	100.00	$J_{n,T}^{(2)}$	10	57.75	83.50	94.65	99.40	100.00	68.65	89.70	97.30	99.85	100.00
		20	73.30	93.05	98.55	99.85	100.00	84.20	97.25	99.65	99.95	100.00		20	27.95	43.80	58.25	72.80	84.10	32.65	50.45	64.00	76.00	84.75
		30	82.45	97.05	99.30	99.95	100.00	89.60	98.65	99.85	100.00	100.00		30	30.35	45.50	58.10	71.70	80.55	35.40	50.70	62.10	74.30	81.15
		50	90.20	98.85	99.90	100.00	100.00	93.90	99.65	99.95	100.00	100.00		50	37.90	56.15	72.50	84.00	88.95	41.55	61.70	75.85	85.20	89.30
		100	95.40	99.65	100.00	100.00	100.00	97.35	99.85	100.00	100.00	100.00		100	41.45	62.75	73.45	83.60	87.75	45.50	66.00	76.20	84.50	88.10
		200	95.80	99.70	100.00	100.00	100.00	97.80	99.85	100.00	100.00	100.00		200	34.50	47.60	54.35	63.10	65.70	35.90	49.55	55.50	64.00	66.00
Bartlett	$S_{n,T}^{(2)}$	10	91.80	98.50	99.85	100.00	100.00	94.55	99.10	99.85	100.00	100.00	$J_{n,T}^{(2)}$	10	83.55	96.20	99.70	100.00	100.00	87.70	97.75	99.80	100.00	100.00
		20	88.85	98.55	99.85	100.00	100.00	92.50	99.05	99.90	100.00	100.00		20	75.75	95.60	99.45	100.00	100.00	82.45	97.90	99.85	100.00	100.00
		30	93.10	99.40	100.00	100.00	100.00	95.75	99.55	100.00	100.00	100.00		30	83.95	98.00	99.80	100.00	100.00	88.20	98.75	99.85	100.00	100.00
		50	95.80	99.80	100.00	100.00	100.00	97.15	99.85	100.00	100.00	100.00		50	91.30	99.75	100.00	100.00	100.00	94.20	99.90	100.00	100.00	100.00
		100	97.70	99.85	100.00	100.00	100.00	98.70	99.95	100.00	100.00	100.00		100	95.30	99.00	99.50	99.75	100.00	96.00	99.10	99.50	99.75	100.00
		200	98.55	99.90	100.00	100.00	100.00	98.95	99.95	100.00	100.00	100.00		200	94.85	98.90	99.00	99.85	100.00	95.25	98.90	99.00	99.85	100.00
Parzen	$S_{n,T}^{(2)}$	10	91.80	98.50	99.85	100.00	100.00	94.55	99.10	99.85	100.00	100.00	$J_{n,T}^{(2)}$	10	83.55	96.20	99.70	100.00	100.00	87.70	97.75	99.80	100.00	100.00
		20	92.30	98.90	99.90	100.00	100.00	95.20	99.25	99.95	100.00	100.00		20	80.25	96.50	99.55	100.00	100.00	84.50	98.00	99.80	100.00	100.00
		30	95.55	99.50	100.00	100.00	100.00	97.50	99.75	100.00	100.00	100.00		30	85.60	98.10	99.75	100.00	100.00	89.50	98.65	99.85	100.00	100.00
		50	97.00	99.85	100.00	100.00	100.00	97.85	99.90	100.00	100.00	100.00		50	91.15	99.40	100.00	100.00	100.00	92.95	99.65	100.00	100.00	100.00
		100	98.40	99.95	100.00	100.00	100.00	99.10	100.00	100.00	100.00	100.00		100	97.80	99.95	100.00	100.00	100.00	98.60	99.95	100.00	100.00	100.00
		200	98.90	99.95	100.00	100.00	100.00	99.40	100.00	100.00	100.00	100.00		200	99.65	100.00	100.00	100.00	100.00	99.95	100.00	100.00	100.00	100.00
Tukey	$S_{n,T}^{(2)}$	10	91.80	98.50	99.85	100.00	100.00	94.55	99.10	99.85	100.00	100.00	$J_{n,T}^{(2)}$	10	83.55	96.20	99.70	100.00	100.00	87.70	97.75	99.80	100.00	100.00
		20	89.55	98.60	99.85	100.00	100.00	92.95	99.10	99.95	100.00	100.00		20	71.40	88.60	92.70	94.00	95.00	76.45	90.45	93.45	94.15	95.00
		30	93.55	99.40	100.00	100.00	100.00	96.15	99.60	100.00	100.00	100.00		30	80.90	93.95	95.95	97.10	97.35	84.65	94.65	96.25	97.20	97.35
		50	96.00	99.80	100.00	100.00	100.00	97.25	99.90	100.00	100.00	100.00		50	84.05	93.00	95.60	96.60	96.70	86.30	93.80	95.80	96.75	96.75
		100	97.70	99.85	100.00	100.00	100.00	98.70	99.95	100.00	100.00	100.00		100	83.20	89.25	91.40	93.35	94.95	83.65	89.45	91.55	93.40	95.00
		200	98.70	99.90	100.00	100.00	100.00	99.10	99.95	100.00	100.00	100.00		200	82.30	89.55	90.20	93.15	93.95	83.05	89.70	90.25	93.20	93.95
QS	$S_{n,T}^{(2)}$	10	90.60	98.20	99.80	100.00	100.00	93.90	98.90	99.85	100.00	100.00	$J_{n,T}^{(2)}$	10	80.40	95.25	99.45	100.00	100.00	85.10	97.00	99.80	100.00	100.00
		20	86.20	97.90	99.75	100.00	100.00	91.30	98.90	99.90	100.00	100.00		20	88.40	99.05	99.85	100.00	100.00	92.70	99.55	100.00	100.00	100.00
		30	91.35	98.95	99.95	100.00	100.00	94.70	99.45	100.00	100.00	100.00		30	94.40	99.55	100.00	100.00	100.00	96.60	99.75	100.00	100.00	100.00
		50	94.60	99.75	100.00	100.00	100.00	96.50	99.85	100.00	100.00	100.00		50	99.00	100.00	100.00	100.00	100.00	99.65	100.00	100.00	100.00	100.00
		100	97.20	99.85	100.00	100.00	100.00	98.25	99.95	100.00	100.00	100.00		100	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
		200	98.00	99.90	100.00	100.00	100.00	98.75	99.95	100.00	100.00	100.00		200	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
	$S_{n,T}^{(3)}$	10	46.95	73.65	91.20	99.00	100.00	66.65	88.75	97.15	99.85	100.00	$J_{n,T}^{(3)}$	10		99.60	99.95	100.00	100.00		99.85	99.95	100.00	100.00
		20	46.90	75.65	91.80	99.25	100.00	66.15	89.65	97.65	99.80	100.00		20			100.00	100.00	100.00			100.00	100.00	100.00
		30	49.70	82.10	93.35	99.70	100.00	70.15	93.05	98.00	99.95	100.00		30				100.00	100.00				100.00	100.00
		50	52.70	82.60	95.75	99.60	100.00	72.70	93.70	99.15	99.95	100.00		50					100.00					100.00
		100	57.60	86.60	96.65	99.90	100.00	77.60	96.15	99.45	100.00	100.00		100										
		200	56.40	87.25	97.30	99.95	100.00	75.95	95.90	99.45	100.00	100.00		200										
Fixed	$S_{n,T}^{(4)}$	10	10.25	56.10	83.55	98.05	100.00	49.40	84.00	95.80	99.75	100.00	$J_{n,T}^{(4)}$	10	8.15	46.65	88.90	99.95	100.00	19.85	76.65	98.50	100.00	100.00
		20	10.20	56.30	86.00	98.80	100.00	48.85	85.45	96.75	99.80	100.00		20	8.95	38.65	76.40	99.80	100.00	18.05	57.55	91.15	100.00	100.00
		30	11.00	63.50	87.95	99.20	100.00	52.60	89.55	97.30	99.90	100.00		30	9.10	38.25	73.10	99.40	100.00	16.35	54.30	86.70	100.00	100.00
		50	12.85	67.45	92.20	99.40	100.00	55.35	90.85	98.50	99.90	100.00		50	13.30	42.20	78.20	99.45	100.00	19.70	54.15	86.25	99.95	100.00
		100	14.70	70.85	93.25	99.85	100.00	60.25	93.35	99.05	100.00	100.00		100	11.30	36.20	71.30	98.25	100.00	16.15	44.80	79.50	99.30	100.00
		200	13.15	72.80	94.40	99.85	100.00	58.60	94.00	99.35	100.00	100.00		200	13.75	41.30	76.20	98.35	100.00	17.85	48.10	81.60	99.10	100.00
Expanding	$S_{n,T}^{(4)}$	10	9.75	55.55	83.25	98.00	100.00	49.05	83.85	95.80	99.75	100.00	$J_{n,T}^{(4)}$	10	12.10	45.20	83.95	99.65	100.00	26.40	74.45	95.85	100.00	100.00
		20	10.20	56.30	86.00	98.80	100.00	48.85	85.45	96.75	99.80	100.00		20	8.95	38.65	76.40	99.80	100.00	18.05	57.55	91.15	100.00	100.00
		30	11.00	63.50	87.95	99.20	100.00	52.60	89.55	97.30	99.90	100.00		30	9.10	38.25	73.10	99.40	100.00	16.35	54.30	86.70	100.00	100.00
		50	12.85	67.45	92.20	99.40	100.00	55.35	90.85	98.50	99.90	100.00		50	13.30	42.20	78.20	99.45	100.00	19.70	54.15	86.25	99.95	100.00
		100	14.75	70.90	93.25	99.85	100.00	60.25	93.35	99.05	100.00	100.00		100	5.35	22.35	53.40	93.35	99.95	8.10	28.90	62.55	95.80	100.00
		200	13.15	72.85	94.35	99.85	100.00	58.55	93.95	99.30	100.00	100.00		200	3.55	14.05	35.55	72.25	95.55	4.80	17.60	40.65	76.30	96.50
Fixed	$S_{n,T}^{(5)}$	10	10.05	55.80	83.50	98.05	100.00	49.30	83.90	95.80	99.75	100.00	$J_{n,T}^{(5)}$	10	5.60	28.10	69.05	89.10	93.75	9.90	53.30	83.95	91.35	94.35
		20	10.05	55.90	85.45	98.80	100.00	48.60	85.25	96.60	99.80	100.00		20	3.25	11.50	31.95	81.00	92.35	4.25	18.25	52.50	86.95	93.00
		30	10.65	62.85	87.75	99.15	100.00	51.65	89.50	97.25	99.90	100.00		30	4.05	9.60	27.45	71.50	90.10	5.15	14.65	41.55	78.85	90.80
		50	12.05	66.60	92.05	99.35	100.00	54.65	90.50	98.50	99.90	100.00		50	3.70	12.75	28.65	68.20	85.80	4.20	16.40	37.40	73.35	86.45
		100	13.60	70.00	93.05	99.85	100.00	59.20	92.90	99.00	100.00	100.00		100	3.20	9.05	23.55	56.95	80.90	3.60	11.15	28.90	62.75	81.75
		200	12.35	71.65	94.25	99.85	100.00	58.00	93.60	99.30	100.00	100.00		200	2.65	6.65	13.90	40.65	77.00	2.90	7.25	15.60	45.45	77.90
Expanding	$S_{n,T}^{(5)}$	10	9.40	55.35	82.85	98.05	100.00	48.85	83.70	95.75	99.75	100.00	$J_{n,T}^{(5)}$	10	21.25	43.50	63.55	80.35	85.00	29.55	57.35	74.50	82.65	86.10
		20	10.15	56.10	85.55	98.80	100.00	48.65	85.35	96.60	99.80	100.00		20	15.60	38.40	61.20	81.60	88.95	19.30	48.00	70.15	84.05	89.35
		30	10.75	62.85	87.85	99.15	100.00	51.85	89.55	97.25	99.90	100.00		30	17.80	36.60	55.90	74.35	83.40	20.75	43.70	62.85	77.65	83.95
		50	12.15	66.65	92.05	99.35	100.00	54.75	90.50	98.50	99.90	100.00		50	16.30	35.85	53.10	72.60	74.70	19.15	39.55	57.15	74.40	75.40
		100	14.05	70.45	93.05	99.85	100.00	59.70	93.10	99.00	100.00	100.00		100	12.35	29.40	45.75	64.05	76.40	13.20	32.05	48.75	66.65	77.15
		200	12.65	72.15	94.30	99.85	100.00	58.25	93.80	99.30	100.00	100.00		200	7.30	16.80	24.65	40.25	60.60	7.75	17.80	26.85	41.60	62.65

Table B11: Power Under Heterogeneous Alternative – DGP 1: No Factor Dependence, No Spatial Dependence

			Overall EPA Test												Joint EPA Test									
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	0.80	0.75	0.80	1.95	2.50	5.65	4.95	5.15	8.05	8.95	$J_{n,T}^{(1)}$	10	6.25	2.95	3.10	3.70	6.70	18.65	10.80	12.20	13.20	19.75
		20	1.35	1.65	1.85	1.65	2.85	5.75	6.05	6.65	6.50	9.50		20	12.60	5.20	5.15	5.40	12.25	28.75	16.70	15.35	17.95	29.95
		30	0.90	1.05	1.85	2.20	2.70	4.75	6.00	6.60	6.85	8.95		30	17.10	6.95	6.00	7.85	16.95	38.10	20.40	18.40	22.60	37.65
		50	1.25	1.30	2.10	2.20	2.90	4.75	6.00	6.65	8.45	10.30		50	25.90	10.35	9.35	11.25	27.60	49.55	27.45	25.75	28.35	50.70
		100	1.10	1.60	1.30	2.10	3.25	5.15	6.65	6.85	7.20	10.60		100	48.85	20.40	17.05	21.75	52.80	73.15	43.10	39.10	45.45	74.00
		200	1.45	1.50	1.65	1.85	4.60	5.85	6.95	8.05	8.10	12.80		200	81.85	39.90	32.85	41.95	85.60	93.70	65.15	58.65	68.30	95.25
Truncated	$S_{n,T}^{(2)}$	10	1.70	1.25	0.85	2.25	2.45	6.80	5.65	5.35	8.15	9.10	$J_{n,T}^{(2)}$	10	31.55	11.40	7.55	6.00	7.75	44.65	23.20	19.50	18.00	21.45
		20	2.35	1.75	1.80	1.65	2.75	7.40	6.65	7.15	7.40	9.70		20	34.90	45.50	41.15	21.55	19.95	40.20	55.10	56.50	38.35	39.95
		30	1.60	1.70	1.80	2.20	2.65	6.00	6.70	6.85	7.40	9.40		30	37.50	49.40	55.65	34.25	30.30	41.80	56.65	68.45	55.15	51.90
		50	1.65	1.35	2.00	2.10	3.00	5.60	6.00	6.85	8.90	10.55		50	37.65	51.30	67.55	54.05	46.00	40.15	56.30	74.75	72.90	68.55
		100	1.35	1.60	1.35	2.25	3.45	5.35	7.05	6.95	7.45	10.70		100	40.30	59.10	81.50	86.00	78.70	42.50	61.50	82.90	94.50	90.85
		200	1.75	1.65	1.50	1.95	4.55	6.60	7.20	8.20	8.45	13.10		200	32.65	42.00	56.30	81.70	99.85	33.75	43.55	57.50	82.75	99.95
Bartlett	$S_{n,T}^{(2)}$	10	0.80	0.75	0.80	1.95	2.50	5.65	4.95	5.15	8.05	8.95	$J_{n,T}^{(2)}$	10	6.25	2.95	3.10	3.70	6.70	18.65	10.80	12.20	13.20	19.75
		20	1.70	1.55	1.95	1.55	2.80	6.10	5.95	6.65	6.70	9.65		20	24.15	8.20	6.50	6.00	12.95	43.25	22.40	17.75	20.10	31.15
		30	0.90	1.40	1.90	2.30	2.65	4.95	5.95	6.45	7.20	9.10		30	33.85	11.40	8.95	9.65	18.20	55.00	28.15	21.75	25.05	39.95
		50	1.30	1.25	2.05	2.15	3.00	4.80	5.90	6.70	8.50	10.55		50	50.85	17.90	14.10	13.75	28.65	71.95	38.95	32.40	32.35	52.80
		100	1.20	1.45	1.45	2.00	3.35	5.20	6.60	6.60	7.15	10.70		100	95.00	52.00	37.40	32.55	58.15	98.35	74.55	62.20	57.30	77.90
		200	1.50	1.55	1.65	1.90	4.65	6.10	6.95	8.25	8.25	13.00		200	100.00	89.65	72.60	67.10	91.40	100.00	96.60	88.45	86.00	97.90
Parzen	$S_{n,T}^{(2)}$	10	0.80	0.75	0.80	1.95	2.50	5.65	4.95	5.15	8.05	8.95	$J_{n,T}^{(2)}$	10	6.25	2.95	3.10	3.70	6.70	18.65	10.80	12.20	13.20	19.75
		20	1.50	1.50	1.90	1.60	2.80	5.70	5.95	6.60	6.55	9.55		20	14.10	5.50	5.35	5.30	12.45	32.30	17.85	15.80	18.65	30.05
		30	0.85	1.15	1.85	2.30	2.70	4.85	5.95	6.60	7.00	9.15		30	20.15	7.80	6.60	8.20	17.25	41.40	21.85	18.85	23.10	38.10
		50	1.25	1.25	2.05	2.15	2.90	4.95	5.95	6.75	8.45	10.45		50	31.10	12.20	10.20	11.90	27.40	53.55	29.85	27.00	29.25	51.30
		100	1.15	1.45	1.50	2.00	3.30	5.15	6.55	6.70	7.10	10.65		100	79.10	34.85	26.20	26.85	55.35	92.20	59.70	49.95	51.70	75.70
		200	1.50	1.55	1.65	1.90	4.65	5.90	6.95	8.10	8.30	12.85		200	99.00	68.60	51.75	53.20	88.40	99.90	86.00	74.85	77.40	97.10
Tukey	$S_{n,T}^{(2)}$	10	0.80	0.75	0.80	1.95	2.50	5.65	4.95	5.15	8.05	8.95	$J_{n,T}^{(2)}$	10	6.25	2.95	3.10	3.70	6.70	18.65	10.80	12.20	13.20	19.75
		20	1.65	1.50	1.95	1.55	2.80	6.05	6.00	6.70	6.65	9.60		20	23.20	7.65	6.65	5.75	12.90	41.80	21.80	17.45	20.10	31.20
		30	0.90	1.35	1.90	2.30	2.65	5.00	5.90	6.45	7.15	9.05		30	31.40	11.10	8.60	9.45	18.25	53.25	27.35	21.30	24.80	39.55
		50	1.30	1.25	1.95	2.15	3.00	4.75	5.90	6.80	8.50	10.50		50	47.75	17.15	13.25	13.55	28.65	69.55	37.35	31.25	31.75	52.75
		100	1.25	1.40	1.45	2.00	3.35	5.10	6.65	6.55	7.15	10.65		100	97.00	56.30	39.45	34.10	59.10	99.10	77.30	64.10	58.60	78.40
		200	1.55	1.55	1.65	1.95	4.70	6.00	7.00	8.10	8.25	12.95		200	100.00	91.85	74.55	68.30	91.55	100.00	97.65	89.60	86.75	97.90
QS	$S_{n,T}^{(2)}$	10	0.85	0.85	0.80	1.95	2.35	5.80	5.15	5.00	8.10	8.95	$J_{n,T}^{(2)}$	10	6.60	3.10	3.00	3.70	6.65	18.70	11.25	11.95	13.70	19.65
		20	1.90	1.65	1.85	1.60	2.75	6.25	6.10	6.85	6.90	9.55		20	39.80	13.15	8.80	7.85	14.05	60.00	29.05	22.50	22.10	32.30
		30	1.10	1.40	1.95	2.25	2.60	5.20	5.90	6.70	7.25	9.00		30	56.10	18.90	12.70	11.65	19.80	74.30	38.35	27.20	29.00	41.80
		50	1.50	1.30	1.95	2.20	3.00	4.95	5.90	6.80	8.50	10.55		50	78.85	30.00	21.00	18.00	31.40	89.55	52.75	41.60	38.45	55.20
		100	1.20	1.55	1.40	2.10	3.35	5.25	6.65	6.65	7.25	10.75		100	99.90	79.35	58.40	43.70	63.65	100.00	91.20	78.35	67.45	81.50
		200	1.55	1.60	1.60	2.00	4.65	6.25	6.95	8.05	8.20	13.05		200	100.00	99.85	94.45	84.10	94.75	100.00	99.95	98.15	95.15	99.10
	$S_{n,T}^{(3)}$	10	3.45	1.80	1.40	2.50	2.70	9.85	8.05	5.85	8.45	9.25	$J_{n,T}^{(3)}$	10		43.00	23.95	14.45	11.70		57.80	41.25	30.55	26.85
		20	4.50	2.45	2.30	1.80	3.25	10.10	7.90	8.30	7.90	10.00		20			85.10	49.65	33.85			91.85	68.30	54.25
		30	3.70	2.75	2.30	2.45	3.00	10.30	8.10	8.15	7.75	9.50		30				92.70	65.80				96.90	81.40
		50	3.60	2.45	2.70	2.85	3.55	9.75	8.40	7.90	9.05	10.95		50					98.00					99.15
		100	4.05	3.05	2.50	2.50	4.00	8.90	8.70	8.60	8.50	11.20		100										
		200	4.35	2.80	2.85	2.55	4.80	10.30	9.45	9.05	9.60	13.75		200										
Fixed	$S_{n,T}^{(4)}$	10	0.60	1.35	0.95	1.90	2.65	5.00	5.10	5.20	7.40	9.25	$J_{n,T}^{(4)}$	10	0.65	1.00	1.65	4.00	7.25	4.30	6.80	9.75	14.30	22.50
		20	0.95	1.05	1.45	1.70	2.50	5.70	5.50	6.55	6.85	9.35		20	0.80	1.25	1.60	3.90	10.55	5.85	7.05	8.50	13.55	27.60
		30	0.60	0.95	1.15	1.70	2.60	4.95	5.50	6.55	7.00	9.10		30	0.95	1.50	1.85	3.90	12.95	5.40	6.25	7.95	15.65	32.95
		50	0.65	1.20	1.75	2.15	2.85	4.05	5.50	6.60	8.75	10.25		50	1.70	1.50	1.80	4.25	19.20	8.20	7.45	8.25	16.55	41.80
		100	0.80	1.45	1.25	2.00	3.40	4.75	6.65	6.95	7.00	10.60		100	4.05	2.40	3.15	5.70	32.70	13.05	9.15	12.35	20.80	57.35
		200	1.05	1.25	1.60	1.70	4.80	5.90	7.10	7.75	8.15	12.80		200	8.70	4.25	4.60	11.60	52.35	18.90	13.70	14.20	27.00	72.35
Expanding	$S_{n,T}^{(4)}$	10	0.60	1.20	0.85	2.00	2.50	4.65	4.70	5.15	7.70	8.95	$J_{n,T}^{(4)}$	10	0.15	1.00	1.05	2.95	6.00	2.80	5.20	7.00	11.80	18.20
		20	0.95	1.05	1.45	1.70	2.50	5.70	5.50	6.55	6.85	9.35		20	0.80	1.25	1.60	3.90	10.55	5.85	7.05	8.50	13.55	27.60
		30	0.60	0.95	1.15	1.70	2.60	4.95	5.50	6.55	7.00	9.10		30	0.95	1.50	1.85	3.90	12.95	5.40	6.25	7.95	15.65	32.95
		50	0.65	1.20	1.75	2.15	2.85	4.05	5.50	6.60	8.75	10.25		50	1.70	1.50	1.80	4.25	19.20	8.20	7.45	8.25	16.55	41.80
		100	0.70	1.70	1.35	2.10	3.35	5.20	6.55	6.85	7.00	10.80		100	8.35	2.45	3.50	5.50	31.15	17.00	9.15	12.05	18.20	55.35
		200	1.00	1.35	1.60	1.80	4.55	5.65	6.65	7.60	8.25	12.95		200	13.60	6.15	4.50	9.40	43.65	23.15	13.95	13.75	23.05	64.30
Fixed	$S_{n,T}^{(5)}$	10	0.40	1.00	0.60	1.80	2.40	4.65	4.75	5.15	7.35	9.30	$J_{n,T}^{(5)}$	10	3.55	0.60	0.90	2.90	6.60	7.10	5.35	7.90	11.85	20.30
		20	0.75	0.70	1.40	1.50	2.80	5.35	5.50	6.95	6.75	9.30		20	6.80	9.20	3.00	2.00	8.10	8.20	15.85	9.65	10.25	24.85
		30	0.30	1.05	1.20	1.70	2.50	4.60	5.75	6.85	6.85	9.20		30	5.80	12.50	6.50	2.80	9.65	7.40	18.70	15.50	12.30	29.45
		50	0.55	1.05	1.65	2.05	2.80	4.20	5.20	6.40	8.55	10.30		50	6.30	15.30	12.15	3.15	14.70	8.45	20.45	22.90	14.95	37.10
		100	0.75	1.45	1.35	2.00	3.30	4.70	6.60	6.85	7.00	10.60		100	6.25	17.15	22.90	4.35	24.20	7.05	21.95	32.90	17.85	51.35
		200	1.10	1.40	1.35	1.75	4.45	6.05	6.70	7.85	8.40	13.15		200	4.00	12.35	19.80	40.40	38.00	4.20	14.15	22.85	50.80	65.10
Expanding	$S_{n,T}^{(5)}$	10	0.50	1.15	0.70	2.00	2.55	4.25	5.05	5.25	7.40	9.20	$J_{n,T}^{(5)}$	10	4.35	0.70	0.75	2.40	5.80	7.65	4.30	5.55	9.90	17.95
		20	0.75	0.70	1.40	1.50	2.80	5.35	5.50	6.95	6.75	9.30		20	6.80	9.20	3.00	2.00	8.10	8.20	15.85	9.65	10.25	24.85
		30	0.30	1.05	1.20	1.70	2.50	4.60	5.75	6.85	6.85	9.20		30	5.80	12.50	6.50	2.80	9.65	7.40	18.70	15.50	12.30	29.45
		50	0.55	1.05	1.65	2.05	2.80	4.20	5.20	6.40	8.55	10.30		50	6.30	15.30	12.15	3.15	14.70	8.45	20.45	22.90	14.95	37.10
		100	0.65	1.85	1.20	2.10	3.35	5.15	6.55	6.85	7.20	10.80		100	6.25	17.00	22.65	4.10	22.90	7.10	20.70	32.95	16.20	49.10
		200	0.75	1.25	1.25	1.60	4.45	5.65	6.40	7.85	8.35	13.20		200	2.35	10.55	20.30	35.65	32.15	2.70	12.15	23.60	47.30	55.75

Table B12: Power Under Heterogeneous Alternative – DGP 1: No Factor Dependence, Low Spatial Dependence

			Overall EPA Test												Joint EPA Test									
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	3.45	4.55	4.50	5.00	6.80	12.75	13.25	13.05	13.75	16.85	$J_{n,T}^{(1)}$	10	8.50	3.95	3.50	4.35	8.15	20.65	12.45	12.40	14.60	20.95
		20	3.80	4.40	5.40	4.35	5.95	11.90	11.95	12.35	13.10	14.95		20	11.35	5.40	5.75	6.30	12.30	27.40	16.70	16.50	19.15	30.10
		30	3.85	3.55	4.75	4.40	5.65	10.15	11.00	12.85	13.60	15.90		30	16.05	7.65	6.75	7.60	17.70	34.50	19.85	18.55	21.95	38.15
		50	3.85	3.50	3.10	4.30	6.15	12.35	11.35	11.20	13.20	14.60		50	25.70	9.85	9.15	12.35	28.35	49.30	27.65	26.35	29.25	53.25
		100	4.45	4.00	5.30	5.70	7.50	11.80	11.80	13.85	14.55	17.55		100	49.80	19.90	16.55	22.70	53.60	72.50	41.35	39.45	44.20	75.55
		200	3.40	4.15	4.15	4.60	6.90	10.15	11.15	11.75	12.90	17.80		200	80.80	41.05	33.95	44.10	83.95	92.50	65.80	60.15	69.75	95.15
Truncated	$S_{n,T}^{(2)}$	10	1.70	2.00	1.40	1.70	2.55	6.90	7.10	6.95	7.10	8.85	$J_{n,T}^{(2)}$	10	26.90	16.00	11.55	9.05	11.50	37.15	28.60	24.10	21.55	25.90
		20	1.85	1.60	2.05	1.90	2.30	7.30	6.50	7.35	7.20	8.45		20	33.10	40.15	44.10	27.00	21.40	39.00	48.60	56.70	45.30	42.00
		30	1.85	1.20	1.35	1.45	2.15	6.10	5.80	7.55	6.90	9.10		30	31.50	42.75	53.65	38.65	32.70	35.80	49.45	64.85	58.85	55.75
		50	1.90	1.25	1.10	1.50	2.30	6.80	5.30	5.55	6.80	8.80		50	35.85	48.55	62.20	58.20	51.50	39.55	53.70	69.35	75.75	72.40
		100	1.05	1.30	1.80	2.10	2.05	6.15	5.85	6.85	7.60	9.20		100	40.45	53.00	76.00	88.80	84.20	41.95	56.25	78.25	95.55	93.75
		200	1.25	1.35	1.35	1.40	3.40	4.80	6.50	6.15	6.65	10.05		200	30.75	44.15	53.60	77.35	99.90	32.05	45.70	55.10	78.60	100.00
Bartlett	$S_{n,T}^{(2)}$	10	3.45	4.55	4.50	5.00	6.80	12.75	13.25	13.05	13.75	16.85	$J_{n,T}^{(2)}$	10	8.50	3.95	3.50	4.35	8.15	20.65	12.45	12.40	14.60	20.95
		20	2.10	2.50	2.75	2.75	3.90	9.00	8.65	9.35	9.95	11.15		20	18.25	7.30	5.85	6.45	12.50	36.15	19.40	17.75	19.15	29.70
		30	2.45	2.15	2.85	2.75	3.20	7.85	8.25	9.60	9.75	12.40		30	26.10	10.35	7.75	7.85	17.90	48.15	23.95	20.15	22.55	38.65
		50	2.50	2.15	1.90	2.55	4.05	9.35	8.05	7.95	9.80	11.45		50	44.80	14.80	11.95	13.00	29.40	66.90	34.05	30.15	31.30	53.90
		100	1.65	1.80	2.70	2.90	3.65	7.60	7.85	8.95	9.30	11.40		100	90.65	42.05	31.60	28.70	56.50	97.00	66.00	55.50	53.45	78.95
		200	1.65	2.15	2.00	2.25	4.45	6.60	7.90	7.75	8.15	12.25		200	100.00	85.95	68.45	64.20	89.45	100.00	95.85	87.30	84.50	97.15
Parzen	$S_{n,T}^{(2)}$	10	3.45	4.55	4.50	5.00	6.80	12.75	13.25	13.05	13.75	16.85	$J_{n,T}^{(2)}$	10	8.50	3.95	3.50	4.35	8.15	20.65	12.45	12.40	14.60	20.95
		20	2.90	3.45	3.85	3.45	4.85	10.25	10.40	10.90	11.00	13.05		20	11.35	5.40	4.90	5.90	11.90	26.95	16.15	15.95	18.25	29.20
		30	3.20	2.65	3.55	3.50	4.55	9.10	9.75	11.15	11.80	13.90		30	15.60	7.55	6.05	7.00	16.90	35.70	19.25	16.95	20.70	37.50
		50	3.05	2.60	2.55	3.40	5.00	10.70	9.75	9.35	11.85	12.75		50	26.85	9.65	8.75	11.60	26.90	50.05	26.90	25.35	28.95	52.45
		100	1.85	2.05	3.20	3.35	4.45	8.15	8.30	9.90	10.80	12.30		100	72.00	27.20	21.10	22.95	53.05	87.85	51.10	43.80	45.70	76.10
		200	1.90	2.35	2.30	2.65	4.85	7.25	8.60	8.20	9.20	12.80		200	97.50	60.45	46.35	50.55	85.75	99.15	81.55	70.95	74.90	95.85
Tukey	$S_{n,T}^{(2)}$	10	3.45	4.55	4.50	5.00	6.80	12.75	13.25	13.05	13.75	16.85	$J_{n,T}^{(2)}$	10	8.50	3.95	3.50	4.35	8.15	20.65	12.45	12.40	14.60	20.95
		20	2.10	2.65	2.80	2.75	3.95	9.10	8.80	9.50	10.05	11.35		20	17.25	6.90	5.45	6.45	12.45	35.20	19.25	17.30	18.65	29.65
		30	2.35	2.10	2.95	2.75	3.20	7.90	8.15	9.65	9.85	12.45		30	24.45	9.60	7.45	7.45	17.70	46.25	23.40	20.15	22.20	38.30
		50	2.45	2.15	1.90	2.60	4.05	9.35	8.10	7.90	9.95	11.45		50	42.70	13.95	11.20	12.95	29.35	64.90	33.10	29.50	30.90	53.65
		100	1.55	1.65	2.60	2.70	3.10	7.30	7.25	8.45	8.90	10.85		100	94.45	48.75	34.80	31.30	58.05	98.05	71.70	59.05	56.25	80.25
		200	1.45	2.00	2.00	2.05	4.30	6.30	7.75	7.55	7.90	11.85		200	100.00	89.40	72.40	67.05	90.20	100.00	97.05	88.65	86.15	97.40
QS	$S_{n,T}^{(2)}$	10	3.00	4.00	4.00	4.40	5.90	11.60	12.10	11.85	12.85	15.45	$J_{n,T}^{(2)}$	10	7.95	3.50	3.60	4.05	7.80	20.20	12.25	11.80	13.85	20.40
		20	1.75	2.05	2.35	2.55	3.20	8.20	7.55	8.45	8.70	10.25		20	31.90	10.90	8.35	7.60	13.40	54.10	26.90	20.70	22.25	31.40
		30	2.10	1.65	2.20	2.20	2.70	6.65	7.40	8.80	8.75	11.15		30	49.85	16.65	10.85	10.25	19.90	67.85	33.55	26.90	26.65	41.20
		50	2.15	1.85	1.60	2.20	3.15	8.15	6.90	6.75	8.75	10.40		50	73.95	26.55	18.75	16.50	32.40	86.90	48.90	39.70	36.45	56.05
		100	1.30	1.50	2.30	2.40	2.65	7.00	6.80	7.70	8.35	10.05		100	99.75	74.00	53.65	42.55	65.20	99.95	89.15	75.25	66.35	83.75
		200	1.40	1.75	1.75	1.55	3.95	5.80	7.20	7.10	7.40	11.00		200	100.00	99.55	94.05	84.55	94.85	100.00	99.95	98.30	95.15	98.65
	$S_{n,T}^{(3)}$	10	3.50	2.25	1.70	1.65	2.15	9.05	7.70	6.75	7.20	8.15	$J_{n,T}^{(3)}$	10		44.90	23.55	14.05	13.45		60.20	40.10	30.75	29.85
		20	3.90	2.60	2.45	2.20	2.50	9.15	8.05	7.65	7.30	8.85		20			87.15	54.85	35.10			92.70	71.30	56.00
		30	3.45	2.20	2.30	1.90	2.10	9.05	7.30	8.60	7.20	9.00		30				92.90	64.80				96.50	80.20
		50	4.60	2.05	1.20	1.95	2.65	11.70	7.75	6.70	8.05	9.10		50					97.60					99.30
		100	3.55	2.45	2.25	2.65	2.75	10.60	7.95	8.70	8.60	10.15		100										
		200	4.65	2.30	1.65	1.90	3.60	10.30	8.45	7.15	7.15	10.45		200										
Fixed	$S_{n,T}^{(4)}$	10	0.60	0.80	0.90	1.05	1.15	4.90	5.45	4.65	5.25	5.95	$J_{n,T}^{(4)}$	10	0.65	1.45	1.90	4.95	11.00	5.45	7.20	10.65	16.20	26.70
		20	0.70	1.60	1.75	1.60	1.80	5.80	6.80	7.15	7.35	8.60		20	0.60	1.30	1.80	3.85	12.90	5.30	6.55	10.35	15.45	29.85
		30	1.00	1.55	2.25	2.05	2.60	5.25	7.15	7.60	8.20	10.05		30	0.95	1.40	2.00	4.40	15.25	5.90	7.90	8.45	15.95	35.95
		50	1.40	1.75	1.70	2.50	3.85	8.55	7.20	7.50	10.20	11.20		50	2.15	1.40	2.80	4.80	21.20	9.55	8.10	10.95	17.50	45.25
		100	1.85	2.60	3.50	4.05	5.25	7.35	8.50	11.00	11.95	14.35		100	4.45	2.85	3.25	8.05	37.00	13.10	10.25	11.40	23.00	62.50
		200	1.80	2.95	3.05	3.35	6.20	7.95	9.20	10.05	11.70	16.00		200	9.85	4.40	4.60	11.95	55.35	19.40	13.65	15.10	28.95	76.80
Expanding	$S_{n,T}^{(4)}$	10	1.30	2.00	1.55	1.70	2.05	6.55	7.60	6.75	7.10	8.25	$J_{n,T}^{(4)}$	10	0.65	1.15	1.65	3.40	8.05	4.30	5.85	8.45	12.55	22.05
		20	0.70	1.60	1.75	1.60	1.80	5.80	6.80	7.15	7.35	8.60		20	0.60	1.30	1.80	3.85	12.90	5.30	6.55	10.35	15.45	29.85
		30	1.00	1.55	2.25	2.05	2.60	5.25	7.15	7.60	8.20	10.05		30	0.95	1.40	2.00	4.40	15.25	5.90	7.90	8.45	15.95	35.95
		50	1.40	1.75	1.70	2.50	3.85	8.55	7.20	7.50	10.20	11.20		50	2.15	1.40	2.80	4.80	21.20	9.55	8.10	10.95	17.50	45.25
		100	1.45	2.20	2.90	3.50	4.60	6.80	7.75	10.25	11.00	13.65		100	8.05	3.40	3.05	7.05	33.45	16.10	11.70	12.70	21.70	60.60
		200	1.85	2.30	2.65	3.35	6.10	6.80	8.90	9.75	10.90	15.25		200	13.50	6.55	4.60	9.70	47.50	21.60	14.30	13.75	24.35	69.45
Fixed	$S_{n,T}^{(5)}$	10	0.45	0.70	0.80	1.10	1.25	4.15	5.15	4.35	5.15	6.50	$J_{n,T}^{(5)}$	10	4.55	1.20	1.60	3.40	8.30	8.45	6.00	7.60	12.50	23.10
		20	0.30	0.90	1.25	1.40	1.55	4.30	5.75	6.20	6.00	8.15		20	6.00	10.15	5.05	2.75	8.75	7.55	16.05	12.65	12.75	26.35
		30	0.45	0.80	1.25	1.40	1.55	4.00	5.05	6.00	5.95	7.60		30	6.60	12.05	10.20	3.95	10.60	7.90	17.30	19.75	15.25	32.35
		50	0.55	0.70	0.70	1.45	2.45	5.75	4.75	5.25	6.90	8.40		50	7.80	13.00	17.10	5.05	17.45	9.50	18.45	27.95	19.15	42.80
		100	0.75	0.75	1.40	2.00	2.10	4.55	5.30	6.55	7.00	9.15		100	6.95	18.00	25.50	7.25	31.15	8.35	23.00	35.90	24.60	59.05
		200	0.90	1.15	0.85	1.50	3.10	4.55	5.90	5.95	6.20	10.00		200	3.20	11.20	18.35	39.70	46.85	3.40	13.05	22.10	50.05	72.65
Expanding	$S_{n,T}^{(5)}$	10	0.85	0.85	0.95	1.05	1.60	4.95	6.00	5.15	5.40	7.05	$J_{n,T}^{(5)}$	10	4.90	1.75	1.85	2.40	6.95	8.80	5.90	8.15	11.20	21.35
		20	0.30	0.90	1.25	1.40	1.55	4.30	5.75	6.20	6.00	8.15		20	6.00	10.15	5.05	2.75	8.75	7.55	16.05	12.65	12.75	26.35
		30	0.45	0.80	1.25	1.40	1.55	4.00	5.05	6.00	5.95	7.60		30	6.60	12.05	10.20	3.95	10.60	7.90	17.30	19.75	15.25	32.35
		50	0.55	0.70	0.70	1.45	2.45	5.75	4.75	5.25	6.90	8.40		50	7.80	13.00	17.10	5.05	17.45	9.50	18.45	27.95	19.15	42.80
		100	0.65	0.70	1.35	1.80	2.15	4.40	5.15	6.65	7.25	9.25		100	5.75	17.55	23.45	6.55	28.00	6.30	21.85	32.35	23.35	56.55
		200	1.25	1.10	0.75	1.40	3.25	4.70	5.95	6.10	6.10	9.90		200	3.20	10.05	19.00	36.55	40.00	3.45	11.55	22.10	45.65	65.15

Table B13: Power Under Heterogeneous Alternative – DGP 1: No Factor Dependence, High Spatial Dependence

			Overall EPA Test												Joint EPA Test										
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size					
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	
	$S_{n,T}^{(1)}$	10	37.90	34.70	34.65	32.60	33.75	51.70	48.40	46.20	46.35	46.30	$J_{n,T}^{(1)}$	10	16.10	13.50	12.10	12.55	15.15	24.50	21.65	19.80	19.40	23.80	
		20	40.20	40.60	40.40	41.60	41.05	51.95	52.30	52.25	53.35	52.05		20	19.90	16.25	14.75	15.40	19.50	29.75	24.55	22.60	24.50	30.40	
		30	40.40	38.45	39.90	40.05	41.30	53.05	51.45	51.70	53.15	52.80		30	23.15	16.55	15.65	17.75	22.85	35.80	26.30	26.15	27.25	36.45	
		50	40.95	38.45	38.80	40.60	38.40	52.10	51.15	51.55	53.25	51.25		50	31.75	20.20	20.15	20.15	31.05	46.00	31.15	31.70	32.70	45.60	
		100	32.90	34.65	35.25	37.40	37.20	46.85	46.90	48.80	50.15	50.05		100	46.20	29.00	26.90	29.60	50.20	61.20	41.55	40.35	42.20	65.20	
		200	38.85	38.10	39.35	40.05	39.85	50.95	50.30	51.00	52.20	51.90		200	69.95	42.75	37.65	44.65	72.40	81.85	58.05	52.20	60.15	85.55	
Truncated	$S_{n,T}^{(2)}$	10	9.15	8.75	8.70	9.20	9.55	21.25	21.55	19.70	18.95	20.05	$J_{n,T}^{(2)}$	10	1.90	0.40	0.70	1.20	4.50	4.55	1.85	2.40	3.40	9.20	
		20	4.85	4.65	3.85	4.05	4.55	14.30	13.80	13.50	12.30	12.90		20	9.80	7.00	6.50	6.65	7.90	12.30	9.55	8.40	8.55	9.20	
		30	3.95	4.15	4.55	4.50	5.45	12.35	12.55	13.60	13.05	14.20		30	13.00	11.45	12.70	14.20	20.00	15.45	13.55	15.30	17.15	23.10	
		50	4.70	4.40	4.00	4.25	4.95	13.45	13.90	12.70	12.75	13.75		50	15.15	14.60	15.30	17.95	19.85	17.25	17.35	17.75	20.25	22.60	
		100	1.75	1.65	1.75	1.40	2.10	7.25	7.05	6.75	8.20	8.60		100	19.90	20.20	24.75	32.50	44.80	22.00	22.85	27.90	35.80	47.00	
		200	2.40	1.55	1.55	1.80	2.25	8.50	7.20	6.55	8.15	8.70		200	21.35	26.05	25.85	32.35	45.80	23.10	27.60	27.95	35.05	47.35	
Bartlett	$S_{n,T}^{(2)}$	10	37.90	34.70	34.65	32.60	33.75	51.70	48.40	46.20	46.35	46.30	$J_{n,T}^{(2)}$	10	16.10	13.50	12.10	12.55	15.15	24.50	21.65	19.80	19.40	23.80	
		20	18.40	19.20	18.85	17.30	17.80	32.10	31.75	31.35	30.60	31.70		20	3.75	2.15	1.95	2.25	6.40	8.65	5.30	4.30	5.70	17.00	
		30	17.35	17.00	18.65	18.75	19.55	32.00	30.65	32.25	30.80	32.90		30	4.65	1.50	1.60	2.00	6.65	10.95	4.65	4.30	6.40	18.85	
		50	18.60	18.95	17.35	18.15	18.70	32.05	30.35	30.55	31.35	29.55		50	6.60	2.00	0.90	2.15	11.10	14.10	4.65	3.15	6.00	26.20	
		100	7.40	7.10	7.10	8.60	8.95	16.65	17.90	18.30	19.25	20.90		100	3.35	0.00	0.00	0.60	33.05	8.75	0.45	0.70	3.30	59.20	
		200	10.05	9.15	8.45	9.70	10.45	21.20	20.75	21.20	20.20	21.30		200	33.55	0.95	1.00	3.20	69.95	53.50	4.40	3.45	12.00	88.10	
Parzen	$S_{n,T}^{(2)}$	10	37.90	34.70	34.65	32.60	33.75	51.70	48.40	46.20	46.35	46.30	$J_{n,T}^{(2)}$	10	16.10	13.50	12.10	12.55	15.15	24.50	21.65	19.80	19.40	23.80	
		20	29.20	29.05	28.95	28.40	29.10	42.50	42.10	41.90	43.35	42.30		20	7.25	5.70	4.20	4.90	8.25	14.90	11.30	9.25	10.05	16.50	
		30	28.05	27.35	29.20	28.45	30.40	42.25	40.75	41.75	41.60	42.85		30	8.65	4.20	4.45	4.90	9.05	15.15	9.65	8.60	11.35	17.65	
		50	29.30	27.50	28.00	28.50	27.55	42.75	40.50	40.10	42.15	40.35		50	9.95	4.50	3.70	5.40	11.85	19.45	9.90	9.05	10.50	23.75	
		100	11.45	12.35	11.90	14.35	14.85	23.25	24.70	25.60	26.45	27.00		100	2.85	0.15	0.20	1.15	30.10	6.80	0.80	1.35	4.25	53.15	
		200	16.55	16.10	15.80	15.80	16.95	29.10	27.75	30.00	29.45	28.75		200	13.70	0.60	0.65	2.55	56.55	28.00	2.55	2.35	9.30	79.20	
Tukey	$S_{n,T}^{(2)}$	10	37.90	34.70	34.65	32.60	33.75	51.70	48.40	46.20	46.35	46.30	$J_{n,T}^{(2)}$	10	16.10	13.50	12.10	12.55	15.15	24.50	21.65	19.80	19.40	23.80	
		20	19.60	20.10	20.25	18.50	18.70	33.35	32.80	32.60	32.25	33.05		20	4.85	3.20	2.60	3.50	10.80	11.40	7.75	6.60	9.55	25.85	
		30	18.50	18.25	19.85	20.15	21.10	33.35	32.70	33.65	32.60	33.80		30	6.35	2.65	2.00	3.55	11.60	13.95	6.10	5.90	9.15	27.70	
		50	19.70	20.00	18.25	19.55	19.90	33.80	31.45	31.90	32.95	30.95		50	8.85	2.35	1.35	3.05	16.40	17.85	5.85	4.85	8.55	35.45	
		100	7.20	6.95	6.75	8.35	8.70	16.20	17.55	17.85	18.90	20.30		100	35.25	5.60	7.45	30.15	95.10	53.60	16.45	20.95	54.25	98.70	
		200	10.15	9.25	8.55	9.75	10.55	21.00	21.15	21.40	20.25	21.40		200	93.50	27.60	20.75	48.75	99.40	96.85	51.75	43.15	73.15	99.95	
QS	$S_{n,T}^{(2)}$	10	32.55	30.45	29.65	28.35	28.90	47.50	43.55	42.45	41.55	42.00	$J_{n,T}^{(2)}$	10	11.10	8.95	8.40	9.35	11.20	18.70	16.05	14.65	14.85	19.35	
		20	13.60	13.50	13.15	12.10	13.05	26.30	26.25	26.45	25.30	24.75		20	7.60	2.65	3.15	6.45	27.70	16.80	8.85	8.60	16.30	47.85	
		30	12.40	12.30	13.50	13.05	14.10	25.00	24.50	26.60	25.25	27.05		30	12.90	3.10	2.55	6.20	30.20	26.00	9.80	9.55	17.60	52.65	
		50	12.65	13.60	12.40	12.40	13.55	25.75	24.65	25.00	25.20	24.30		50	24.05	4.30	2.90	7.80	45.50	41.80	12.75	11.10	22.10	68.70	
		100	4.90	4.45	4.40	4.95	5.90	12.05	13.05	12.55	15.10	15.55		100	82.60	29.60	34.00	67.45	99.60	92.80	54.20	57.75	85.70	99.95	
		200	6.45	4.45	4.70	5.95	6.75	16.00	15.05	14.55	14.75	16.25		200	100.00	91.75	77.80	90.25	99.95	100.00	97.55	91.25	97.65	100.00	
	$S_{n,T}^{(3)}$	10	2.65	1.55	1.20	1.30	1.85	8.00	6.65	6.50	6.30	6.50	$J_{n,T}^{(3)}$	10		60.70	50.60	54.75	81.10		74.70	69.80	73.05	90.00	
		20	2.40	1.90	1.70	1.00	1.40	9.15	7.20	6.05	5.80	6.10		20			94.90	83.10	89.35			97.70	92.95	95.80	
		30	2.35	1.45	1.65	1.40	1.50	7.50	6.55	6.10	5.80	6.25		30				98.55	96.95				99.25	99.20	
		50	3.05	1.70	1.30	1.25	1.80	9.90	7.55	5.40	5.95	6.60		50					99.95					100.00	
		100	3.20	2.00	1.75	1.55	1.65	9.55	7.35	6.35	6.85	6.90		100											
		200	4.35	2.25	1.25	1.40	1.55	10.45	6.60	6.00	6.65	6.80		200											
Fixed	$S_{n,T}^{(4)}$	10	0.00	0.30	0.50	0.65	1.35	2.90	3.55	4.30	5.00	5.65	$J_{n,T}^{(4)}$	10	3.40	8.00	14.75	31.75	70.90	11.00	21.40	33.35	54.95	85.35	
		20	0.15	0.60	0.60	0.60	0.90	2.85	3.75	4.05	4.55	5.15		20	4.00	6.80	11.10	17.00	47.45	11.95	15.50	22.30	33.75	68.35	
		30	0.30	0.60	0.95	1.10	0.65	3.80	4.15	4.75	4.45	5.25		30	4.30	8.40	9.95	16.65	39.75	12.05	18.00	20.80	31.05	59.15	
		50	0.85	1.25	0.95	0.90	1.35	5.95	6.55	5.25	5.45	5.90		50	6.50	7.90	10.10	19.25	41.90	14.35	16.80	22.15	33.20	62.10	
		100	5.20	6.30	7.25	8.50	8.00	13.65	15.20	17.55	17.95	19.25		100	10.20	12.15	16.00	24.50	51.75	19.40	21.30	28.80	37.55	67.15	
		200	6.90	8.25	8.15	9.00	10.95	14.50	17.05	18.50	20.15	21.50		200	14.00	13.60	16.70	30.45	70.90	23.40	24.90	28.75	45.40	85.65	
Expanding	$S_{n,T}^{(4)}$	10	0.20	0.40	0.65	0.55	1.10	3.40	4.10	4.40	4.85	5.50	$J_{n,T}^{(4)}$	10	4.70	7.05	9.95	14.55	32.10	12.55	16.05	19.35	27.25	51.15	
		20	0.15	0.60	0.60	0.60	0.90	2.85	3.75	4.05	4.55	5.15		20	4.00	6.80	11.10	17.00	47.45	11.95	15.50	22.30	33.75	68.35	
		30	0.30	0.60	0.95	1.10	0.65	3.80	4.15	4.75	4.45	5.25		30	4.30	8.40	9.95	16.65	39.75	12.05	18.00	20.80	31.05	59.15	
		50	0.85	1.25	0.95	0.90	1.35	5.95	6.55	5.25	5.45	5.90		50	6.50	7.90	10.10	19.25	41.90	14.35	16.80	22.15	33.20	62.10	
		100	2.15	3.80	3.80	4.70	4.75	8.75	10.85	11.30	12.55	13.65		100	13.10	12.30	17.05	26.70	56.20	20.95	22.50	28.15	41.10	73.50	
		200	3.60	4.45	4.60	4.45	6.55	10.80	12.00	12.50	14.15	15.20		200	17.30	15.60	17.50	30.35	75.45	25.70	25.55	29.40	47.35	86.90	
Fixed	$S_{n,T}^{(5)}$	10	0.00	0.30	0.50	0.65	1.25	2.90	3.50	4.25	4.95	5.60	$J_{n,T}^{(5)}$	10	6.30	9.65	13.85	30.35	68.95	10.90	22.65	31.80	53.70	85.80	
		20	0.00	0.60	0.60	0.50	0.70	2.45	3.60	3.90	4.10	4.60		20	5.45	9.20	10.10	15.55	30.30	7.45	12.50	15.40	24.95	46.50	
		30	0.00	0.35	0.45	0.75	0.50	2.50	2.85	3.65	3.70	3.85		30	5.15	10.75	13.40	21.60	42.55	6.15	13.85	18.55	29.40	52.85	
		50	0.15	0.40	0.20	0.40	0.75	3.15	3.55	3.20	3.45	3.95		50	6.05	10.00	17.40	25.05	51.60	7.35	12.80	21.15	31.20	57.55	
		100	0.20	0.90	0.90	1.50	1.25	4.95	4.95	5.25	5.80	5.45		100	5.55	12.25	17.75	30.90	57.00	6.35	14.35	21.40	36.90	60.90	
		200	0.85	0.65	0.95	1.05	1.25	5.70	5.35	4.80	5.60	6.30		200	3.70	10.60	15.25	25.25	55.00	4.00	11.75	17.10	28.25	58.70	
Expanding	$S_{n,T}^{(5)}$	10	0.10	0.20	0.35	0.45	0.95	2.70	2.90	3.75	4.10	4.90	$J_{n,T}^{(5)}$	10	3.25	3.95	4.85	7.30	10.15	5.40	7.00	8.35	12.05	17.50	
		20	0.00	0.60	0.60	0.50	0.70	2.45	3.60	3.90	4.10	4.60		20	5.45	9.20	10.10	15.55	30.30	7.45	12.50	15.40	24.95	46.50	
		30	0.00	0.35	0.45	0.75	0.50	2.50	2.85	3.65	3.70	3.85		30	5.15	10.75	13.40	21.60	42.55	6.15	13.85	18.55	29.40	52.85	
		50	0.15	0.40	0.20	0.40	0.75	3.15	3.55	3.20	3.45	3.95		50	6.05	10.00	17.40	25.05	51.60	7.35	12.80	21.15	31.20	57.55	
		100	0.50	0.95	0.80	0.95	1.20	4.00	4.80	4.95	4.95	5.40		100	5.10	12.70	19.00	34.85	59.80	5.60	14.80	22.45	40.80	64.25	
		200	0.45	0.85	0.75	1.00	1.05	5.65	4.60	4.60	4.95	5.85		200	3.60	7.90	14.25	27.25	55.60	3.85	8.60	15.80	30.85	59.30	

Table B14: Power Under Heterogeneous Alternative – DGP 2: Factor Dependence, No Spatial Dependence

			Overall EPA Test												Joint EPA Test									
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	33.55	31.20	32.05	31.70	32.90	45.25	44.30	44.85	43.40	44.80	$J_{n,T}^{(1)}$	10	17.80	13.15	13.30	12.90	16.95	26.05	20.05	21.05	20.25	27.10
		20	48.85	46.40	47.35	46.90	47.40	59.50	57.65	58.65	57.10	59.50		20	23.85	18.50	17.40	18.75	23.10	30.50	24.10	24.25	25.60	32.25
		30	56.45	55.80	54.40	53.75	54.00	66.00	65.40	64.25	64.30	63.70		30	24.70	21.70	19.90	21.65	26.70	31.40	26.40	25.95	28.35	36.15
		50	63.90	64.70	62.95	64.60	64.15	71.10	71.85	71.50	72.20	72.60		50	30.35	25.30	22.70	24.70	35.15	35.65	30.00	28.15	31.00	42.30
		100	75.45	72.70	74.45	75.25	75.25	82.15	79.15	80.35	80.95	80.40		100	35.25	27.65	28.85	31.65	40.45	39.80	31.15	32.50	36.30	47.55
		200	81.50	81.50	82.20	81.30	81.10	85.80	85.05	86.40	85.40	85.75		200	40.40	34.60	34.15	33.50	47.75	43.40	38.55	37.10	37.10	51.80
Truncated	$S_{n,T}^{(2)}$	10	14.90	13.05	12.45	12.20	12.90	26.85	23.50	23.85	23.70	25.30	$J_{n,T}^{(2)}$	10	11.55	7.70	7.10	6.80	7.05	15.60	10.70	10.00	9.70	10.10
		20	13.10	11.05	9.15	10.55	9.60	24.00	21.60	20.65	19.90	20.05		20	17.05	14.20	11.90	14.70	19.55	20.15	17.55	14.90	18.35	23.45
		30	17.15	16.45	14.45	15.25	13.85	28.90	28.40	27.75	27.15	25.80		30	15.35	14.85	15.10	15.75	21.10	18.35	17.00	17.60	18.25	24.70
		50	28.45	26.15	23.40	24.20	25.60	40.55	39.85	36.35	37.70	37.15		50	17.85	14.50	13.60	17.30	22.05	20.30	17.00	15.20	19.10	24.50
		100	41.60	37.85	38.15	39.10	37.00	52.95	49.55	49.85	51.55	51.45		100	19.55	15.55	15.35	16.15	21.80	21.35	16.80	16.95	17.75	24.05
		200	45.90	44.90	43.05	41.00	42.55	56.60	55.35	54.50	53.40	52.95		200	18.00	15.30	16.50	18.05	22.80	18.95	16.20	17.75	19.10	23.90
Bartlett	$S_{n,T}^{(2)}$	10	33.55	31.20	32.05	31.70	32.90	45.25	44.30	44.85	43.40	44.80	$J_{n,T}^{(2)}$	10	17.80	13.15	13.30	12.90	16.95	26.05	20.05	21.05	20.25	27.10
		20	29.85	27.85	28.25	27.70	28.05	42.80	41.15	42.00	40.95	40.75		20	18.20	10.60	8.95	10.80	19.10	26.45	17.25	15.30	20.05	34.10
		30	36.95	35.55	35.85	35.25	34.65	49.60	48.40	47.55	46.80	48.50		30	20.70	12.50	11.25	13.50	25.40	29.45	18.25	17.75	21.35	41.95
		50	48.20	48.95	45.55	46.85	46.95	58.70	59.20	56.00	58.70	58.05		50	26.60	15.40	14.55	17.75	39.45	34.25	21.20	21.95	26.45	56.10
		100	56.65	53.45	53.55	55.50	55.60	66.70	63.10	64.35	65.70	66.15		100	42.60	21.05	20.10	27.35	68.75	52.00	28.80	29.70	39.55	82.65
		200	64.60	62.95	61.50	60.10	60.35	71.70	71.90	70.95	68.65	69.15		200	66.90	35.55	33.70	44.50	94.50	74.30	45.10	44.55	58.20	98.00
Parzen	$S_{n,T}^{(2)}$	10	33.55	31.20	32.05	31.70	32.90	45.25	44.30	44.85	43.40	44.80	$J_{n,T}^{(2)}$	10	17.80	13.15	13.30	12.90	16.95	26.05	20.05	21.05	20.25	27.10
		20	39.60	37.40	38.05	38.55	38.05	51.95	49.55	50.70	49.45	50.85		20	17.80	12.85	10.50	12.20	16.50	24.45	18.20	16.60	19.15	26.00
		30	47.15	45.10	44.10	43.60	46.50	59.35	58.80	56.90	56.20	56.35		30	18.25	13.85	12.75	14.55	19.70	24.95	19.50	18.15	20.75	30.95
		50	56.80	57.45	54.45	56.70	56.45	65.25	66.15	64.40	65.70	65.85		50	24.10	16.85	15.35	17.90	28.55	28.90	21.35	20.55	23.35	38.90
		100	63.65	59.95	59.80	62.10	62.80	71.60	68.50	69.45	70.95	70.90		100	32.00	19.65	18.75	24.05	50.70	39.45	25.05	25.00	32.20	66.25
		200	70.90	70.75	70.00	67.65	68.30	77.10	76.90	76.80	75.80	75.55		200	41.35	26.15	26.10	29.50	75.10	47.40	31.90	32.15	39.30	86.40
Tukey	$S_{n,T}^{(2)}$	10	33.55	31.20	32.05	31.70	32.90	45.25	44.30	44.85	43.40	44.80	$J_{n,T}^{(2)}$	10	17.80	13.15	13.30	12.90	16.95	26.05	20.05	21.05	20.25	27.10
		20	31.25	29.45	29.15	29.15	29.75	44.20	42.55	43.20	42.10	42.05		20	19.45	11.10	9.45	12.05	21.10	28.05	18.55	17.15	21.75	36.35
		30	38.55	37.50	37.05	36.55	36.20	51.20	50.55	49.20	48.50	49.90		30	22.60	13.60	11.85	14.70	27.85	31.80	20.25	19.50	23.10	43.75
		50	49.15	50.65	47.15	48.50	48.60	59.65	60.35	57.65	59.35	58.85		50	28.20	16.45	15.50	18.70	41.15	37.35	23.85	22.70	27.85	57.00
		100	57.10	53.85	53.75	55.60	55.90	66.95	63.35	64.50	65.95	66.20		100	69.65	35.50	34.80	45.15	87.65	78.55	46.35	47.05	59.75	94.55
		200	65.55	64.25	63.15	61.15	61.35	72.45	72.45	71.65	69.35	70.45		200	91.80	73.35	68.10	80.30	99.60	92.75	83.50	79.25	89.65	99.90
QS	$S_{n,T}^{(2)}$	10	30.85	28.35	29.45	28.15	30.15	42.80	41.05	41.80	40.65	42.30	$J_{n,T}^{(2)}$	10	16.20	11.50	11.10	11.15	14.60	23.70	18.35	19.30	18.10	25.50
		20	25.65	23.40	23.15	22.05	22.70	38.15	35.70	36.25	36.40	36.05		20	31.00	15.90	12.90	18.15	34.60	44.25	26.00	24.55	31.00	53.65
		30	31.40	31.10	30.90	30.15	29.20	45.35	42.95	42.25	41.75	43.25		30	40.25	19.05	18.05	23.05	47.35	53.00	31.75	30.15	37.05	66.25
		50	43.70	43.70	40.55	42.15	41.05	54.75	55.30	52.40	53.70	54.10		50	54.10	28.30	26.70	33.05	69.90	65.95	42.30	38.95	49.30	84.25
		100	52.05	48.90	49.20	50.60	50.30	63.35	59.45	59.45	61.25	62.10		100	94.55	58.50	56.50	67.30	97.00	97.25	72.55	70.75	82.00	99.40
		200	58.35	57.65	56.55	55.60	55.60	68.40	68.20	66.70	64.70	64.70		200	100.00	96.45	94.15	97.25	100.00	100.00	98.55	97.50	99.45	100.00
	$S_{n,T}^{(3)}$	10	3.70	2.65	1.65	1.85	1.40	10.15	7.65	7.50	7.00	6.50	$J_{n,T}^{(3)}$	10		56.85	38.05	31.40	47.30		70.35	56.00	51.65	67.85
		20	4.00	1.85	1.75	1.95	1.50	10.00	7.55	6.20	6.50	6.15		20			92.70	79.30	86.35			96.05	90.10	94.55
		30	3.50	1.70	1.45	1.55	1.20	8.85	6.85	5.95	6.45	5.20		30				99.00	97.95				99.60	99.65
		50	3.75	2.10	1.50	1.90	0.90	9.60	7.20	6.20	7.05	5.90		50					100.00					100.00
		100	3.75	2.85	1.75	1.85	1.20	10.00	7.95	5.75	6.35	5.00		100										
		200	4.00	1.95	1.75	1.35	1.50	10.25	7.40	6.90	5.55	4.70		200										
Fixed	$S_{n,T}^{(4)}$	10	0.35	0.75	0.75	1.20	1.00	3.80	5.05	5.30	5.45	5.60	$J_{n,T}^{(4)}$	10	1.15	4.15	9.85	18.10	48.60	7.75	16.75	26.15	39.45	70.00
		20	0.15	0.35	0.80	1.15	1.35	4.25	4.15	4.55	5.60	5.55		20	2.40	5.45	13.35	29.05	75.30	9.55	19.25	32.90	54.55	88.65
		30	0.20	0.50	0.55	1.05	0.90	3.85	4.05	4.35	5.40	4.65		30	2.95	7.05	16.45	41.70	88.95	11.05	22.15	37.85	66.85	96.55
		50	0.20	0.75	0.55	1.15	0.65	4.40	4.25	4.65	6.00	5.40		50	5.40	10.90	26.15	62.15	98.30	16.15	28.35	49.20	82.50	99.45
		100	0.05	1.05	0.80	1.20	1.00	4.40	5.35	4.70	5.40	4.80		100	11.15	22.05	48.30	87.85	100.00	24.60	43.95	69.55	95.70	100.00
		200	0.15	0.75	0.65	0.95	1.30	4.50	5.10	5.20	4.60	4.35		200	24.90	40.70	71.35	98.25	100.00	38.40	59.90	84.25	99.50	100.00
Expanding	$S_{n,T}^{(4)}$	10	0.30	0.75	0.65	1.15	0.95	3.70	4.95	5.20	5.35	5.50	$J_{n,T}^{(4)}$	10	1.45	3.90	8.15	13.35	40.15	7.60	14.45	21.65	31.40	62.95
		20	0.15	0.35	0.80	1.15	1.35	4.25	4.15	4.55	5.60	5.55		20	2.40	5.45	13.35	29.05	75.30	9.55	19.25	32.90	54.55	88.65
		30	0.20	0.50	0.55	1.05	0.90	3.85	4.05	4.35	5.40	4.65		30	2.95	7.05	16.45	41.70	88.95	11.05	22.15	37.85	66.85	96.55
		50	0.20	0.75	0.55	1.15	0.65	4.40	4.25	4.65	6.00	5.40		50	5.40	10.90	26.15	62.15	98.30	16.15	28.35	49.20	82.50	99.45
		100	0.05	1.05	0.80	1.20	1.00	4.40	5.35	4.70	5.40	4.80		100	10.55	10.05	18.05	38.15	59.90	21.15	22.15	32.85	55.35	73.95
		200	0.15	0.75	0.65	0.95	1.30	4.50	5.10	5.20	4.60	4.35		200	15.40	12.90	16.85	20.65	5.80	21.40	21.00	24.95	26.40	8.70
Fixed	$S_{n,T}^{(5)}$	10	0.35	0.75	0.75	1.25	1.00	3.95	5.10	5.45	5.45	5.65	$J_{n,T}^{(5)}$	10	4.35	2.75	7.40	14.60	43.30	10.25	13.45	23.00	34.80	67.10
		20	0.15	0.40	0.85	1.15	1.35	4.45	4.30	4.55	5.70	5.65		20	6.05	11.80	8.75	16.95	66.50	8.60	21.10	23.95	42.70	84.30
		30	0.20	0.50	0.55	1.05	0.90	3.95	4.10	4.35	5.50	4.70		30	6.05	13.85	16.65	27.80	82.40	8.40	21.30	35.35	55.30	94.10
		50	0.20	0.80	0.55	1.15	0.65	4.40	4.25	4.65	6.00	5.40		50	6.85	17.40	28.45	44.90	96.60	8.45	24.35	47.80	73.55	99.15
		100	0.05	1.05	0.80	1.20	1.00	4.40	5.35	4.70	5.40	4.80		100	6.90	19.85	41.85	72.80	99.95	8.40	25.80	58.80	90.60	100.00
		200	0.15	0.75	0.65	0.95	1.30	4.50	5.10	5.20	4.60	4.35		200	3.60	13.70	25.60	76.70	100.00	3.85	15.40	30.50	82.85	100.00
Expanding	$S_{n,T}^{(5)}$	10	0.30	0.75	0.70	1.20	1.00	3.80	5.05	5.45	5.50	5.55	$J_{n,T}^{(5)}$	10	4.95	4.70	7.50	13.70	38.50	10.50	14.45	21.95	31.80	62.85
		20	0.15	0.40	0.85	1.15	1.35	4.45	4.30	4.55	5.70	5.65		20	6.05	11.80	8.75	16.95	66.50	8.60	21.10	23.95	42.70	84.30
		30	0.20	0.50	0.55	1.05	0.90	3.95	4.10	4.35	5.50	4.70		30	6.05	13.85	16.65	27.80	82.40	8.40	21.30	35.35	55.30	94.10
		50	0.20	0.80	0.55	1.15	0.65	4.40	4.25	4.65	6.00	5.40		50	6.85	17.40	28.45	44.90	96.60	8.45	24.35	47.80	73.55	99.15
		100	0.05	1.05	0.80	1.20	1.00	4.40	5.35	4.70	5.40	4.80		100	6.40	15.50	25.50	24.50	53.30	7.00	19.35	36.25	43.75	69.90
		200	0.15	0.75	0.65	0.95	1.30	4.50	5.10	5.20	4.60	4.35		200	3.05	9.60	13.35	24.40	4.10	3.10	10.65	16.15	28.85	5.30

Table B15: Power Under Heterogeneous Alternative – DGP 2: Factor Dependence, Low Spatial Dependence

			Overall EPA Test												Joint EPA Test									
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	34.80	35.20	33.20	31.35	37.65	47.40	46.70	45.40	44.50	48.20	$J_{n,T}^{(1)}$	10	18.05	15.65	13.45	13.55	19.35	25.35	22.35	20.80	19.40	29.20
		20	50.20	49.95	49.20	47.60	46.80	61.50	61.25	59.95	58.65	57.35		20	23.65	18.80	19.05	18.10	23.20	30.40	25.95	25.00	24.30	31.30
		30	56.50	53.95	55.20	55.95	56.40	66.95	64.20	64.45	64.95	65.15		30	26.60	20.75	22.85	23.55	26.50	31.75	26.20	28.00	29.35	35.70
		50	64.15	64.45	63.05	65.90	64.10	71.80	72.05	71.75	73.30	73.05		50	30.35	25.00	23.25	26.80	31.55	36.65	29.85	28.45	32.85	39.90
		100	74.45	73.50	74.40	72.85	74.15	79.90	80.45	81.30	79.30	80.10		100	34.80	29.95	29.15	29.05	40.35	39.00	33.55	33.55	34.10	47.60
		200	80.00	80.95	81.30	81.15	81.90	84.30	85.40	85.10	86.40	85.60		200	38.75	33.05	30.75	34.65	47.60	41.45	35.70	33.35	38.55	52.95
Truncated	$S_{n,T}^{(2)}$	10	14.30	13.35	11.00	11.00	13.05	24.40	24.25	22.30	20.45	25.00	$J_{n,T}^{(2)}$	10	6.40	3.05	2.00	1.90	4.25	10.55	6.05	4.00	4.55	8.75
		20	12.05	10.10	9.50	7.70	8.70	22.25	21.40	19.90	18.55	18.45		20	12.55	10.80	13.10	13.70	19.75	15.55	13.05	16.00	16.10	24.45
		30	17.80	14.00	15.55	15.30	13.50	29.15	26.70	28.35	26.65	25.15		30	13.35	13.20	12.35	14.65	20.00	15.70	15.50	14.25	17.30	23.45
		50	26.40	24.45	23.15	24.20	21.50	39.30	36.10	35.10	36.40	34.65		50	12.80	10.55	10.20	13.00	16.60	15.10	12.20	11.70	15.35	18.40
		100	37.70	37.65	37.10	34.20	35.10	50.45	49.20	50.10	46.95	48.40		100	16.40	13.15	13.05	14.55	21.70	18.00	14.50	14.65	16.45	23.45
		200	42.85	41.20	41.15	40.25	41.25	53.35	52.30	51.80	52.60	54.35		200	14.90	14.80	12.75	16.40	21.85	15.60	15.90	13.75	17.75	23.20
Bartlett	$S_{n,T}^{(2)}$	10	34.80	35.20	33.20	31.35	37.65	47.40	46.70	45.40	44.50	48.20	$J_{n,T}^{(2)}$	10	18.05	15.65	13.45	13.55	19.35	25.35	22.35	20.80	19.40	29.20
		20	28.40	29.15	26.90	25.40	25.00	41.75	41.40	40.65	38.75	38.15		20	13.60	8.95	8.00	8.05	18.80	20.35	13.45	14.00	14.90	33.75
		30	36.75	34.40	36.20	34.80	33.15	49.15	46.20	48.50	48.15	47.55		30	16.95	9.70	10.35	10.70	25.10	22.90	14.85	15.85	19.85	41.75
		50	47.80	44.15	43.60	45.30	43.75	57.85	55.85	55.25	58.10	56.15		50	20.80	12.90	12.25	15.65	36.50	27.50	17.20	17.45	24.55	55.25
		100	54.10	53.25	53.20	51.70	52.80	63.95	64.30	63.30	62.15	64.00		100	30.95	16.30	15.00	21.95	74.50	38.15	22.75	22.90	32.50	86.90
		200	59.70	59.05	58.80	59.60	60.35	68.25	69.00	68.45	68.05	69.10		200	48.40	24.80	23.75	40.95	96.50	56.95	30.85	31.90	52.65	98.95
Parzen	$S_{n,T}^{(2)}$	10	34.80	35.20	33.20	31.35	37.65	47.40	46.70	45.40	44.50	48.20	$J_{n,T}^{(2)}$	10	18.05	15.65	13.45	13.55	19.35	25.35	22.35	20.80	19.40	29.20
		20	38.60	38.20	38.25	36.60	35.55	52.30	51.40	51.20	49.05	48.85		20	15.20	11.35	10.50	9.05	15.10	21.85	15.65	16.30	15.75	24.30
		30	47.15	44.10	46.95	45.65	44.85	58.15	55.30	55.90	56.95	57.30		30	17.90	11.75	12.60	13.40	18.50	23.10	16.35	17.65	19.85	28.05
		50	56.25	54.40	54.15	56.75	54.90	64.80	65.50	63.35	66.35	65.10		50	21.40	14.95	14.20	16.25	22.25	25.55	18.85	18.25	21.95	31.45
		100	60.10	60.00	59.60	57.75	59.55	69.05	68.50	68.70	67.60	69.05		100	25.40	16.75	16.10	18.90	57.75	30.35	21.45	20.80	26.90	73.30
		200	67.40	67.05	66.95	67.30	68.20	74.25	75.50	75.05	74.45	75.85		200	32.40	20.45	19.05	28.75	81.75	36.70	24.75	24.10	36.85	91.15
Tukey	$S_{n,T}^{(2)}$	10	34.80	35.20	33.20	31.35	37.65	47.40	46.70	45.40	44.50	48.20	$J_{n,T}^{(2)}$	10	18.05	15.65	13.45	13.55	19.35	25.35	22.35	20.80	19.40	29.20
		20	29.65	30.20	28.40	26.90	26.65	42.90	42.95	41.95	40.40	39.75		20	15.55	10.80	9.55	10.00	24.00	23.75	16.70	16.40	18.75	40.80
		30	38.25	36.50	37.65	36.45	34.40	50.50	47.25	49.65	49.50	49.40		30	20.40	11.40	12.35	14.30	33.00	27.40	17.35	19.35	24.45	49.15
		50	48.75	46.00	44.80	47.15	45.55	58.95	57.40	56.75	59.35	57.60		50	26.10	15.55	14.10	19.70	46.00	33.15	21.10	21.45	30.15	65.10
		100	54.20	53.45	53.35	51.80	53.05	63.90	64.35	63.30	62.25	64.15		100	64.70	38.50	40.35	57.70	97.85	74.25	49.90	54.80	73.60	99.35
		200	60.55	59.85	60.05	60.80	61.35	69.20	69.60	69.20	69.05	70.25		200	85.20	74.80	76.05	93.35	100.00	86.90	83.80	85.40	97.40	100.00
QS	$S_{n,T}^{(2)}$	10	31.05	32.35	28.90	26.75	34.45	43.30	43.60	41.30	40.95	45.30	$J_{n,T}^{(2)}$	10	15.20	12.75	10.65	11.00	15.75	22.00	18.60	16.85	17.05	26.45
		20	23.45	23.25	21.95	20.25	20.65	36.10	35.20	35.40	33.00	33.15		20	23.90	14.30	14.15	17.35	44.50	36.30	23.80	24.75	32.95	63.55
		30	31.65	28.60	30.85	29.15	27.90	44.30	41.55	43.95	43.05	40.45		30	31.95	16.65	17.75	26.15	60.65	44.15	27.35	29.85	44.35	78.65
		50	42.45	39.50	37.80	40.25	38.25	53.90	51.80	50.55	53.10	50.95		50	45.70	25.30	25.70	40.25	82.30	57.25	36.90	36.80	56.75	93.00
		100	49.20	48.55	49.10	45.70	47.65	59.80	59.40	58.90	56.90	58.85		100	91.35	64.00	65.65	83.20	99.80	95.60	76.60	79.75	92.05	99.95
		200	54.80	54.45	53.20	54.30	56.20	64.55	63.65	63.50	64.25	64.80		200	100.00	97.60	96.65	99.75	100.00	100.00	99.10	98.85	99.95	100.00
	$S_{n,T}^{(3)}$	10	4.80	2.60	1.45	1.90	1.80	10.25	8.70	6.70	6.10	6.55	$J_{n,T}^{(3)}$	10		61.85	49.20	48.35	72.00		73.45	65.65	65.05	83.80
		20	3.45	2.20	2.05	1.45	1.40	9.60	7.70	6.75	5.25	6.20		20			95.90	90.85	95.45			98.00	96.25	98.25
		30	3.95	1.90	1.85	1.30	1.35	10.10	6.40	7.45	5.75	5.70		30				99.65	99.65				99.80	99.90
		50	3.25	2.25	1.50	1.30	1.30	8.55	6.75	6.75	5.45	4.70		50					100.00					100.00
		100	3.30	1.90	1.25	1.95	0.75	8.65	7.05	5.70	5.45	4.95		100										
		200	4.05	2.05	1.60	1.35	1.70	10.00	7.15	6.05	6.25	4.90		200										
Fixed	$S_{n,T}^{(4)}$	10	0.10	0.50	0.60	0.85	1.10	4.95	5.30	4.65	4.85	5.65	$J_{n,T}^{(4)}$	10	2.15	7.40	12.65	26.95	64.10	10.10	20.90	31.20	49.30	81.20
		20	0.15	0.90	0.85	0.85	1.20	3.60	5.05	4.70	4.15	5.50		20	3.25	8.20	15.35	36.15	80.45	11.20	21.50	35.45	59.30	92.15
		30	0.30	0.70	0.85	0.75	1.05	4.15	4.35	5.70	4.65	5.00		30	4.80	10.15	19.30	46.50	91.10	13.35	24.75	41.40	69.95	97.25
		50	0.15	1.05	0.35	0.75	0.85	3.55	4.55	4.55	4.25	4.50		50	7.00	14.30	28.80	66.15	98.30	17.65	30.80	50.40	85.05	99.55
		100	0.05	0.55	0.35	1.20	0.60	3.75	4.55	4.45	5.05	4.60		100	13.70	23.90	48.75	87.70	100.00	26.45	43.25	70.40	95.50	100.00
		200	0.40	0.50	0.75	0.80	1.35	4.30	4.30	4.80	5.60	4.60		200	25.65	43.70	72.00	97.95	100.00	37.60	60.40	83.75	99.30	100.00
Expanding	$S_{n,T}^{(4)}$	10	0.10	0.50	0.55	0.85	1.10	4.85	5.25	4.65	4.80	5.40	$J_{n,T}^{(4)}$	10	2.45	6.15	10.80	18.60	50.25	10.15	17.20	24.35	38.00	70.80
		20	0.15	0.90	0.85	0.85	1.20	3.60	5.05	4.70	4.15	5.50		20	3.25	8.20	15.35	36.15	80.45	11.20	21.50	35.45	59.30	92.15
		30	0.30	0.70	0.85	0.75	1.05	4.15	4.35	5.70	4.65	5.00		30	4.80	10.15	19.30	46.50	91.10	13.35	24.75	41.40	69.95	97.25
		50	0.15	1.05	0.35	0.75	0.85	3.55	4.55	4.55	4.25	4.50		50	7.00	14.30	28.80	66.15	98.30	17.65	30.80	50.40	85.05	99.55
		100	0.05	0.55	0.35	1.20	0.60	3.80	4.55	4.45	5.05	4.60		100	13.35	16.10	34.50	74.30	99.85	23.70	31.95	52.95	86.50	100.00
		200	0.40	0.50	0.75	0.80	1.35	4.30	4.30	4.80	5.60	4.60		200	20.85	22.40	36.90	65.05	87.75	27.70	33.90	48.90	73.70	92.35
Fixed	$S_{n,T}^{(5)}$	10	0.10	0.60	0.55	0.85	1.10	4.90	5.30	4.65	4.80	5.60	$J_{n,T}^{(5)}$	10	6.65	7.30	11.55	25.15	63.95	12.40	20.30	30.05	47.90	81.15
		20	0.15	0.90	0.85	0.80	1.15	3.55	5.00	4.55	4.10	5.40		20	6.20	11.85	20.10	45.30	86.65	8.75	19.95	35.00	63.80	93.85
		30	0.25	0.60	0.85	0.75	0.90	4.10	4.15	5.60	4.65	4.95		30	6.75	15.45	24.85	56.70	95.80	8.85	21.50	37.60	75.25	98.70
		50	0.15	1.00	0.35	0.65	0.75	3.50	4.35	4.40	4.20	4.40		50	7.60	16.80	30.40	76.70	99.60	9.20	22.85	42.55	85.80	100.00
		100	0.00	0.55	0.35	1.15	0.60	3.60	4.50	4.45	5.00	4.55		100	5.80	21.05	42.65	90.35	100.00	7.55	25.85	53.20	93.30	100.00
		200	0.35	0.50	0.70	0.80	1.30	4.25	4.30	4.80	5.60	4.60		200	4.30	12.80	26.45	65.30	99.85	4.50	15.10	30.80	70.05	99.85
Expanding	$S_{n,T}^{(5)}$	10	0.05	0.50	0.55	0.75	1.05	4.70	4.95	4.45	4.75	5.30	$J_{n,T}^{(5)}$	10	6.65	9.10	13.20	24.10	58.85	11.35	20.35	30.75	45.15	77.45
		20	0.15	0.90	0.85	0.80	1.15	3.55	5.00	4.55	4.10	5.40		20	6.20	11.85	20.10	45.30	86.65	8.75	19.95	35.00	63.80	93.85
		30	0.25	0.60	0.85	0.75	0.90	4.10	4.15	5.60	4.65	4.95		30	6.75	15.45	24.85	56.70	95.80	8.85	21.50	37.60	75.25	98.70
		50	0.15	1.00	0.35	0.65	0.75	3.50	4.35	4.40	4.20	4.40		50	7.60	16.80	30.40	76.70	99.60	9.20	22.85	42.55	85.80	100.00
		100	0.00	0.55	0.35	1.15	0.60	3.65	4.50	4.45	5.00	4.60		100	5.35	17.25	36.05	81.15	99.95	6.15	21.30	45.45	88.50	100.00
		200	0.40	0.50	0.70	0.80	1.30	4.25	4.30	4.80	5.60	4.60		200	1.95	10.45	18.65	46.90	90.50	2.10	11.55	22.10	53.65	94.35

Table B16: Power Under Heterogeneous Alternative – DGP 2: Factor Dependence, High Spatial Dependence

			Overall EPA Test												Joint EPA Test										
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S^{(1)}_{n,T}$	10	41.00	40.35	38.15	37.60	42.00	52.85	51.50	49.50	49.75	53.20	$J^{(1)}_{n,T}$	10	17.75	17.45	15.00	14.85	19.85	24.25	22.85	20.70	21.10	28.45
		20	54.55	54.30	54.45	52.55	51.30	65.25	63.85	64.00	63.55	61.40		20	23.35	20.80	20.40	20.45	23.65	28.35	26.30	25.75	26.55	30.85
		30	60.65	58.80	60.55	59.80	58.45	69.70	67.45	68.40	68.20	68.40		30	26.50	22.80	23.70	24.95	25.85	31.15	27.40	28.85	29.45	33.15
		50	67.70	67.50	65.45	68.40	66.40	75.30	75.15	73.95	75.80	74.15		50	30.85	25.75	24.70	26.80	30.55	34.70	29.80	29.10	31.60	38.35
		100	74.30	74.70	75.95	73.85	74.20	79.10	80.60	81.75	79.80	80.05		100	35.25	30.35	29.35	30.05	39.50	39.15	34.25	33.65	34.60	46.80
		200	79.95	80.95	80.80	81.05	82.10	84.60	84.80	85.70	85.70	86.10		200	38.40	32.65	31.05	35.70	46.70	41.15	36.20	34.55	38.10	52.20
Truncated	$S^{(2)}_{n,T}$	10	14.95	15.30	12.30	12.30	14.60	27.30	26.20	24.05	23.05	26.75	$J^{(2)}_{n,T}$	10	6.30	4.95	3.15	6.45	14.85	10.00	8.45	7.10	11.00	21.55
		20	12.35	10.60	9.80	9.15	8.70	22.40	21.90	20.80	20.10	19.35		20	4.30	4.30	5.15	5.95	7.25	5.35	5.45	6.00	6.95	8.30
		30	17.20	14.00	14.70	14.60	12.05	28.65	26.35	27.85	27.00	23.65		30	6.25	5.05	5.05	5.60	8.05	7.20	5.75	5.80	6.50	9.50
		50	24.95	23.45	21.95	21.90	20.85	36.90	34.55	34.10	35.30	33.25		50	6.30	5.35	5.20	7.50	11.55	7.30	6.20	6.10	8.50	13.20
		100	33.65	33.45	33.05	30.80	31.00	46.70	46.20	46.70	43.90	45.20		100	5.50	4.55	5.65	7.70	12.65	6.00	5.25	6.45	8.55	14.15
		200	38.85	37.60	37.35	36.70	37.25	50.30	49.90	48.90	49.10	50.35		200	8.95	8.85	7.70	11.35	16.90	9.45	9.45	8.40	12.60	17.75
Bartlett	$S^{(2)}_{n,T}$	10	41.00	40.35	38.15	37.60	42.00	52.85	51.50	49.50	49.75	53.20	$J^{(2)}_{n,T}$	10	17.75	17.45	15.00	14.85	19.85	24.25	22.85	20.70	21.10	28.45
		20	31.35	30.50	29.50	28.05	27.50	44.40	44.10	43.90	42.40	40.40		20	9.25	6.80	7.55	8.80	24.45	13.15	10.80	11.90	15.45	39.65
		30	38.80	35.45	37.60	36.45	34.40	49.95	49.05	49.30	48.35	46.85		30	11.55	7.55	9.45	11.85	33.65	16.30	11.20	13.65	19.70	50.70
		50	47.15	43.95	43.85	46.05	43.90	59.30	56.40	54.35	58.15	55.75		50	13.95	10.20	10.65	16.95	53.50	18.75	13.85	15.15	25.10	69.15
		100	50.60	50.90	51.55	48.05	50.85	61.85	61.10	61.70	60.20	60.90		100	17.95	12.95	14.50	33.15	95.70	21.45	16.60	20.65	45.15	98.65
		200	56.90	56.40	56.70	57.30	58.35	65.95	65.90	66.45	67.30	67.05		200	25.60	20.65	23.45	59.35	99.60	29.55	24.60	30.05	72.00	99.60
Parzen	$S^{(2)}_{n,T}$	10	41.00	40.35	38.15	37.60	42.00	52.85	51.50	49.50	49.75	53.20	$J^{(2)}_{n,T}$	10	17.75	17.45	15.00	14.85	19.85	24.25	22.85	20.70	21.10	28.45
		20	43.20	43.15	42.60	41.05	39.15	54.60	54.20	54.30	52.55	51.05		20	12.95	10.20	10.40	10.05	13.85	17.30	14.10	14.05	14.45	21.10
		30	49.10	48.20	48.70	47.35	46.05	60.20	58.40	60.20	59.35	57.60		30	15.40	11.05	12.15	12.50	15.65	19.20	13.90	15.50	16.90	23.30
		50	58.80	55.90	54.25	57.50	55.55	67.10	66.60	64.45	67.50	65.35		50	17.20	12.30	11.85	14.25	19.60	20.90	15.55	15.40	18.25	26.65
		100	58.75	57.55	58.10	56.50	58.35	67.60	67.40	68.05	66.65	67.85		100	15.85	12.50	13.40	23.45	83.95	19.80	16.05	18.30	32.20	92.10
		200	65.40	65.25	65.45	66.40	66.20	72.20	73.40	73.80	73.95	74.15		200	21.10	15.60	18.30	37.20	98.25	24.45	18.15	22.65	45.30	99.15
Tukey	$S^{(2)}_{n,T}$	10	41.00	40.35	38.15	37.60	42.00	52.85	51.50	49.50	49.75	53.20	$J^{(2)}_{n,T}$	10	17.75	17.45	15.00	14.85	19.85	24.25	22.85	20.70	21.10	28.45
		20	32.70	32.10	31.15	30.10	28.95	46.00	46.05	45.25	43.55	42.30		20	13.70	13.35	15.85	21.10	33.20	18.35	16.85	20.60	27.15	41.05
		30	40.15	36.65	38.60	37.75	35.90	51.40	50.25	51.20	49.95	48.10		30	16.60	13.35	16.65	22.05	39.20	22.50	18.25	22.85	29.50	47.80
		50	49.40	45.65	45.70	48.00	45.70	60.60	58.20	56.00	59.85	57.60		50	20.15	18.65	20.00	29.85	48.70	23.95	22.65	24.10	36.60	55.45
		100	50.60	51.05	51.65	48.15	51.05	62.20	61.50	61.70	60.45	61.10		100	43.85	54.30	60.65	67.15	74.30	47.00	57.00	62.95	68.25	75.05
		200	57.75	57.50	57.55	58.40	59.35	67.10	66.80	67.15	68.25	68.35		200	48.45	56.10	60.35	69.70	74.50	50.70	58.10	61.55	70.50	74.95
QS	$S^{(2)}_{n,T}$	10	36.30	36.55	33.95	32.90	37.80	49.20	48.20	45.55	45.55	49.40	$J^{(2)}_{n,T}$	10	14.95	13.90	11.10	12.25	16.60	19.75	19.35	16.70	17.20	25.10
		20	24.90	24.35	23.20	23.30	22.35	38.05	38.60	37.30	35.35	33.90		20	19.60	19.10	28.90	52.00	86.35	29.60	30.85	43.00	68.70	93.70
		30	32.25	29.40	31.85	30.15	27.25	44.30	42.25	43.55	43.20	41.00		30	28.45	24.25	37.40	66.05	95.45	37.85	35.50	51.90	80.00	98.10
		50	41.05	38.80	38.35	40.00	38.05	53.90	50.65	49.95	53.25	51.25		50	38.50	35.45	50.20	84.15	99.45	48.80	49.60	64.25	92.05	99.80
		100	45.45	45.30	45.85	42.45	44.15	56.95	56.10	56.60	54.75	56.65		100	91.55	95.75	99.60	100.00	100.00	95.50	98.20	99.85	100.00	100.00
		200	51.55	51.60	51.10	51.00	52.85	61.75	61.45	61.25	62.50	62.30		200	100.00	99.90	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
	$S^{(3)}_{n,T}$	10	4.55	2.50	1.60	1.85	1.70	10.30	8.90	6.00	5.80	6.80	$J^{(3)}_{n,T}$	10		96.20	97.05	98.65	99.95		97.70	98.60	99.65	100.00
		20	3.65	2.10	1.70	1.55	1.60	9.30	7.40	6.90	6.25	6.10		20			100.00	100.00	100.00			100.00	100.00	100.00
		30	4.30	2.05	1.90	1.25	1.25	9.75	6.40	7.35	5.85	5.70		30				100.00	100.00				100.00	100.00
		50	3.10	2.15	1.30	1.00	0.75	9.20	7.15	6.15	5.65	5.00		50					100.00					100.00
		100	3.00	1.60	1.10	2.00	0.90	8.75	7.10	5.85	5.85	5.10		100										
		200	3.55	1.80	1.85	1.40	1.70	9.70	6.85	6.20	6.15	5.50		200										
Fixed	$S^{(4)}_{n,T}$	10	0.10	0.70	0.65	1.15	1.40	4.95	6.00	4.55	5.00	6.05	$J^{(4)}_{n,T}$	10	10.00	33.45	59.05	84.05	97.70	24.80	56.35	77.90	93.45	98.95
		20	0.20	0.85	0.75	0.85	1.30	3.95	5.10	5.70	4.85	5.55		20	10.95	26.60	51.55	84.85	99.70	22.55	47.50	71.30	94.50	100.00
		30	0.35	0.55	0.80	0.80	1.10	4.95	4.10	5.65	4.95	5.15		30	12.55	26.00	46.65	83.80	99.90	24.60	44.15	66.40	93.85	100.00
		50	0.25	0.85	0.50	0.60	0.60	3.55	4.25	4.75	4.45	4.55		50	14.75	29.50	47.70	84.70	99.80	25.85	43.65	66.45	93.60	99.95
		100	0.05	0.70	0.45	1.15	0.60	3.55	4.35	4.30	5.15	4.85		100	21.50	31.10	50.10	81.95	100.00	30.20	43.05	63.40	91.00	100.00
		200	0.25	0.55	0.75	0.95	1.50	4.20	4.20	4.75	5.10	5.05		200	27.05	43.95	64.90	94.40	100.00	35.55	56.35	75.50	97.60	100.00
Expanding	$S^{(4)}_{n,T}$	10	0.10	0.65	0.65	1.10	1.35	4.80	5.85	4.50	4.90	6.00	$J^{(4)}_{n,T}$	10	8.10	17.75	31.65	57.70	91.65	20.20	35.60	51.45	75.95	96.60
		20	0.20	0.85	0.75	0.85	1.30	3.95	5.10	5.70	4.85	5.55		20	10.95	26.60	51.55	84.85	99.70	22.55	47.50	71.30	94.50	100.00
		30	0.35	0.55	0.80	0.80	1.10	4.95	4.10	5.65	4.95	5.15		30	12.55	26.00	46.65	83.80	99.90	24.60	44.15	66.40	93.85	100.00
		50	0.25	0.85	0.50	0.60	0.60	3.55	4.25	4.75	4.45	4.55		50	14.75	29.50	47.70	84.70	99.80	25.85	43.65	66.45	93.60	99.95
		100	0.05	0.70	0.45	1.15	0.60	3.55	4.35	4.35	5.20	4.85		100	22.65	33.60	54.80	89.90	100.00	32.70	45.20	68.55	95.35	100.00
		200	0.25	0.55	0.75	0.95	1.50	4.20	4.25	4.80	5.10	5.05		200	30.00	44.00	67.45	96.05	100.00	37.00	55.80	76.75	98.00	100.00
Fixed	$S^{(5)}_{n,T}$	10	0.10	0.70	0.65	1.10	1.40	4.95	6.00	4.55	5.05	6.00	$J^{(5)}_{n,T}$	10	9.95	34.15	52.85	70.85	79.40	17.30	49.55	64.45	76.25	81.45
		20	0.20	0.70	0.75	0.85	1.25	3.90	4.95	5.45	4.80	5.35		20	5.75	18.20	38.05	61.90	77.20	7.90	26.30	49.40	68.95	78.90
		30	0.35	0.50	0.75	0.70	1.05	4.65	3.95	5.60	4.85	4.90		30	6.35	18.25	32.95	53.85	70.60	8.50	23.80	42.00	60.10	72.75
		50	0.25	0.85	0.35	0.60	0.60	3.40	4.00	4.50	4.35	4.45		50	7.80	17.15	31.10	46.95	64.40	8.95	21.00	36.55	51.60	65.90
		100	0.00	0.55	0.40	1.15	0.55	3.15	3.85	3.85	4.90	4.70		100	5.05	15.05	22.45	36.30	51.40	5.65	16.90	25.40	40.20	53.40
		200	0.25	0.40	0.70	0.80	1.40	3.95	4.00	4.50	5.00	4.60		200	4.55	13.55	21.50	35.75	51.60	4.90	14.75	24.05	37.50	52.40
Expanding	$S^{(5)}_{n,T}$	10	0.10	0.60	0.65	1.10	1.30	4.70	5.60	4.40	4.85	5.75	$J^{(5)}_{n,T}$	10	9.00	20.00	30.95	49.70	64.95	14.20	29.10	41.80	58.65	69.25
		20	0.20	0.70	0.75	0.85	1.25	3.90	4.95	5.45	4.80	5.35		20	5.75	18.20	38.05	61.90	77.20	7.90	26.30	49.40	68.95	78.90
		30	0.35	0.50	0.75	0.70	1.05	4.65	3.95	5.60	4.85	4.90		30	6.35	18.25	32.95	53.85	70.60	8.50	23.80	42.00	60.10	72.75
		50	0.25	0.85	0.35	0.60	0.60	3.40	4.00	4.50	4.35	4.45		50	7.80	17.15	31.10	46.95	64.40	8.95	21.00	36.55	51.60	65.90
		100	0.00	0.55	0.40	1.15	0.55	3.25	4.05	4.00	4.95	4.75		100	5.30	16.30	29.00	47.40	60.40	5.85	18.75	31.85	50.35	61.80
		200	0.25	0.50	0.70	0.80	1.40	4.00	4.05	4.55	5.00	4.65		200	3.95	12.35	22.70	43.00	59.85	4.30	13.70	25.30	45.15	60.90

Table B17: Size Adjusted Power Under Homogeneous Alternative – DGP 1: No Factor Dependence, No Spatial Dependence

			Overall EPA Test												Joint EPA Test									
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	6.00	10.70	19.65	30.80	59.30	16.00	27.10	38.65	50.65	80.55	$J_{n,T}^{(1)}$	10	0.80	2.00	3.10	6.55	22.50	6.55	9.80	12.55	18.90	46.25
		20	10.15	22.20	32.70	61.05	92.95	25.70	45.50	55.70	82.25	97.95		20	1.45	2.65	5.85	16.25	38.80	6.30	11.75	15.65	31.55	63.35
		30	15.85	35.90	53.75	79.15	99.40	36.30	60.70	76.95	94.10	99.90		30	2.00	4.45	5.80	17.90	59.60	7.65	13.70	19.80	39.65	83.05
		50	27.85	60.05	77.75	96.60	100.00	52.25	80.80	93.55	99.20	100.00		50	1.55	4.35	11.55	25.95	81.15	9.25	15.65	27.05	48.60	93.20
		100	61.90	93.05	99.00	100.00	100.00	83.90	98.00	100.00	100.00	100.00		100	2.35	5.15	19.10	53.40	96.65	10.35	22.55	41.80	77.40	99.45
		200	92.90	99.95	100.00	100.00	100.00	97.50	100.00	100.00	100.00	100.00		200	3.50	17.20	36.00	80.90	99.95	13.65	39.25	61.20	94.20	100.00
Truncated	$S_{n,T}^{(2)}$	10	4.35	10.40	18.80	29.00	57.80	15.25	26.00	38.35	50.50	80.95	$J_{n,T}^{(2)}$	10	0.50	1.50	3.10	4.85	21.15	2.95	7.60	10.10	18.30	46.35
		20	6.80	21.85	31.55	60.05	91.45	24.60	43.05	56.30	82.10	98.00		20	0.85	0.45	1.00	8.35	33.35	3.25	3.15	5.55	25.50	58.65
		30	12.50	32.60	52.85	77.20	99.30	34.05	58.45	77.10	93.35	99.95		30	0.85	0.55	0.80	7.40	51.85	2.80	2.65	5.40	27.80	78.00
		50	25.05	58.20	78.80	96.35	100.00	50.90	81.85	93.65	99.05	100.00		50	0.60	0.20	0.60	12.90	74.25	3.05	3.20	3.30	36.90	90.50
		100	60.00	93.45	98.95	100.00	100.00	82.55	97.95	99.95	100.00	100.00		100	0.25	0.35	0.35	31.05	95.25	2.40	2.75	4.20	56.05	98.85
		200	91.30	100.00	100.00	100.00	100.00	97.45	100.00	100.00	100.00	100.00		200	0.65	0.50	0.65	0.35	99.80	2.45	2.20	2.70	5.65	99.90
Bartlett	$S_{n,T}^{(2)}$	10	6.00	10.70	19.65	30.80	59.30	16.00	27.10	38.65	50.65	80.55	$J_{n,T}^{(2)}$	10	0.80	2.00	3.10	6.55	22.50	6.55	9.80	12.55	18.90	46.25
		20	9.15	21.80	30.65	61.45	92.85	24.15	44.70	56.15	82.80	98.00		20	1.20	2.30	4.85	13.95	38.05	6.75	10.85	15.30	32.65	63.00
		30	15.55	35.55	54.25	79.10	99.45	35.35	61.40	77.45	94.10	99.95		30	1.85	4.15	6.05	17.00	58.95	7.35	12.90	19.25	38.20	82.45
		50	28.30	60.15	78.25	96.20	100.00	52.85	80.95	93.65	99.10	100.00		50	1.40	4.50	11.90	24.40	81.90	7.65	14.00	24.15	47.05	93.30
		100	61.00	93.20	99.15	100.00	100.00	83.50	98.00	99.95	100.00	100.00		100	1.95	6.55	16.65	45.00	96.15	10.30	21.35	38.30	74.60	99.45
		200	92.90	99.95	100.00	100.00	100.00	97.55	100.00	100.00	100.00	100.00		200	3.35	14.65	36.00	80.15	99.95	11.95	32.00	58.30	92.60	100.00
Parzen	$S_{n,T}^{(2)}$	10	6.00	10.70	19.65	30.80	59.30	16.00	27.10	38.65	50.65	80.55	$J_{n,T}^{(2)}$	10	0.80	2.00	3.10	6.55	22.50	6.55	9.80	12.55	18.90	46.25
		20	9.35	22.05	32.45	61.55	92.95	25.40	45.75	55.65	82.20	98.00		20	1.50	2.70	5.05	15.10	38.80	6.50	11.80	15.95	32.55	63.70
		30	15.40	35.45	53.70	79.55	99.40	36.00	61.35	77.25	94.20	99.90		30	1.50	4.00	5.75	18.25	60.45	7.65	13.60	19.75	39.15	83.00
		50	28.05	59.85	77.85	96.50	100.00	52.60	80.85	93.65	99.15	100.00		50	1.50	4.35	11.75	25.45	81.45	8.80	14.75	26.10	47.50	92.95
		100	60.45	93.10	99.15	100.00	100.00	83.65	97.90	99.95	100.00	100.00		100	1.90	6.65	18.50	47.55	96.55	10.45	21.70	39.20	75.55	99.45
		200	93.00	99.95	100.00	100.00	100.00	97.60	100.00	100.00	100.00	100.00		200	3.00	16.35	40.05	80.40	100.00	11.75	33.55	60.00	93.65	100.00
Tukey	$S_{n,T}^{(2)}$	10	6.00	10.70	19.65	30.80	59.30	16.00	27.10	38.65	50.65	80.55	$J_{n,T}^{(2)}$	10	0.80	2.00	3.10	6.55	22.50	6.55	9.80	12.55	18.90	46.25
		20	9.10	21.70	31.00	61.60	92.90	24.45	44.80	55.95	82.55	98.00		20	1.30	2.35	4.70	14.15	38.20	6.70	10.90	15.55	32.90	63.75
		30	14.90	35.45	54.25	79.20	99.45	35.20	61.50	77.55	94.15	99.95		30	1.85	4.15	5.95	17.05	59.00	7.45	13.35	19.65	38.50	82.30
		50	28.30	60.30	78.00	96.25	100.00	52.60	80.65	93.70	99.10	100.00		50	1.35	4.75	11.40	24.75	81.50	7.60	14.80	24.70	46.45	93.10
		100	60.85	93.20	99.20	100.00	100.00	83.50	97.95	99.95	100.00	100.00		100	2.20	6.60	16.00	43.80	96.15	8.75	19.95	38.20	73.85	99.45
		200	92.85	99.95	100.00	100.00	100.00	97.70	100.00	100.00	100.00	100.00		200	2.90	14.30	35.95	80.20	99.95	11.75	31.25	57.05	92.50	100.00
QS	$S_{n,T}^{(2)}$	10	5.80	10.75	19.85	30.95	59.25	15.85	27.45	38.85	50.25	80.95	$J_{n,T}^{(2)}$	10	0.85	2.15	3.10	6.60	22.70	6.90	9.35	12.50	19.45	46.75
		20	8.70	21.10	30.70	60.90	92.20	24.05	44.60	56.40	82.60	98.00		20	1.15	2.15	4.80	13.95	37.25	6.45	10.00	14.80	31.65	62.95
		30	14.60	34.65	54.20	78.75	99.40	34.75	60.60	77.50	93.75	99.95		30	1.90	3.75	5.40	16.10	58.40	6.75	13.25	18.05	36.60	81.65
		50	28.15	60.10	79.80	96.20	100.00	52.25	80.95	93.60	99.10	100.00		50	1.95	5.05	9.95	23.10	80.90	6.15	13.55	24.20	47.25	92.95
		100	60.90	93.15	99.15	100.00	100.00	82.85	97.95	99.95	100.00	100.00		100	2.15	6.20	15.70	43.10	95.70	8.65	18.85	35.45	73.70	99.30
		200	92.50	99.95	100.00	100.00	100.00	97.65	100.00	100.00	100.00	100.00		200	2.45	9.60	31.00	78.10	99.95	9.50	28.35	53.75	90.85	100.00
	$S_{n,T}^{(3)}$	10	4.95	9.15	15.15	30.65	57.70	12.50	25.05	36.10	49.15	79.15	$J_{n,T}^{(3)}$	10		1.55	2.55	4.85	20.15		7.60	8.70	15.15	42.85
		20	5.35	18.80	30.45	61.40	92.65	20.75	41.95	52.05	81.35	98.00		20			1.80	7.70	26.55			9.75	21.45	55.90
		30	9.30	26.85	53.60	76.05	99.25	27.95	54.80	77.15	92.85	99.95		30				4.55	38.20				18.55	64.65
		50	18.75	49.00	75.20	95.65	100.00	45.50	76.00	92.75	98.95	100.00		50					38.55					70.95
		100	43.70	84.30	98.40	100.00	100.00	73.15	96.40	99.85	100.00	100.00		100										
		200	76.65	99.90	100.00	100.00	100.00	93.95	100.00	100.00	100.00	100.00		200										
Fixed	$S_{n,T}^{(4)}$	10	3.25	5.85	15.25	25.15	57.80	11.95	23.50	34.45	45.20	80.05	$J_{n,T}^{(4)}$	10	0.75	1.40	2.55	3.95	16.00	4.80	7.25	8.10	13.30	37.35
		20	5.30	19.70	29.65	56.55	90.95	19.95	41.00	55.65	81.45	98.05		20	1.20	2.25	3.40	8.40	26.40	5.70	7.50	11.55	22.35	53.65
		30	8.65	24.85	53.80	75.20	99.10	29.45	58.40	76.60	93.15	99.90		30	0.90	2.20	4.00	6.05	44.45	4.80	8.30	13.70	25.75	68.55
		50	19.75	51.50	74.80	96.30	100.00	47.05	77.90	93.40	99.10	100.00		50	1.25	2.45	4.75	18.05	55.00	5.50	8.00	15.35	29.55	77.35
		100	46.00	87.05	98.95	100.00	100.00	78.30	97.15	99.90	100.00	100.00		100	1.00	3.00	5.20	19.55	68.30	4.45	8.80	15.85	40.15	83.00
		200	82.60	100.00	100.00	100.00	100.00	95.55	100.00	100.00	100.00	100.00		200	0.75	3.20	6.30	20.75	39.60	4.35	8.90	18.30	33.75	52.50
Expanding	$S_{n,T}^{(4)}$	10	4.20	6.30	17.75	27.30	56.95	13.20	24.60	36.20	47.70	79.10	$J_{n,T}^{(4)}$	10	1.35	1.75	2.35	4.25	18.60	5.70	7.90	10.45	16.10	39.35
		20	5.30	19.70	29.65	56.55	90.95	19.95	41.00	55.65	81.45	98.05		20	1.20	2.25	3.40	8.40	26.40	5.70	7.50	11.55	22.35	53.65
		30	8.65	24.85	53.80	75.20	99.10	29.45	58.40	76.60	93.15	99.90		30	0.90	2.20	4.00	6.05	44.45	4.80	8.30	13.70	25.75	68.55
		50	19.75	51.50	74.80	96.30	100.00	47.05	77.90	93.40	99.10	100.00		50	1.25	2.45	4.75	18.05	55.00	5.50	8.00	15.35	29.55	77.35
		100	41.95	85.20	98.75	100.00	100.00	76.40	97.10	99.90	100.00	100.00		100	0.65	1.85	4.15	12.60	53.40	2.60	5.65	9.90	28.30	72.40
		200	78.45	99.95	100.00	100.00	100.00	95.25	100.00	100.00	100.00	100.00		200	0.55	1.45	3.15	11.60	25.70	3.70	5.40	9.85	19.70	37.60
Fixed	$S_{n,T}^{(5)}$	10	3.40	6.45	15.05	24.80	57.40	12.65	23.70	34.25	46.70	79.25	$J_{n,T}^{(5)}$	10	0.45	1.35	2.25	4.65	15.55	3.30	6.85	10.00	13.30	37.45
		20	5.05	19.50	30.60	58.20	91.65	19.45	40.90	53.35	81.70	98.05		20	0.65	0.45	1.05	6.10	22.60	3.35	3.25	7.05	20.80	51.00
		30	9.80	27.75	52.30	74.70	99.35	30.20	57.30	76.05	92.95	99.90		30	0.30	0.25	0.25	5.55	37.15	3.00	2.50	4.85	21.50	64.25
		50	18.15	51.35	74.65	96.15	100.00	46.95	78.20	92.90	98.95	100.00		50	0.55	0.45	0.50	8.10	48.45	2.80	2.70	3.60	22.85	77.20
		100	43.85	87.15	98.70	100.00	100.00	77.15	97.10	99.90	100.00	100.00		100	0.50	0.30	0.15	8.40	61.20	2.40	3.15	2.60	24.85	79.20
		200	81.20	100.00	100.00	100.00	100.00	95.10	100.00	100.00	100.00	100.00		200	0.80	0.65	0.60	0.30	29.80	3.10	2.85	2.90	3.05	40.65
Expanding	$S_{n,T}^{(5)}$	10	7.00	9.85	23.80	30.05	62.50	16.35	28.80	40.25	52.15	83.00	$J_{n,T}^{(5)}$	10	0.85	5.35	10.25	11.60	29.65	6.00	16.80	22.10	27.75	53.90
		20	7.90	25.40	37.10	64.10	93.55	24.30	45.15	58.30	84.55	98.55		20	0.20	0.85	2.20	24.60	46.85	3.65	5.60	25.35	46.10	72.80
		30	14.15	35.10	59.80	80.75	99.55	35.45	61.85	79.80	94.20	99.90		30	0.80	0.55	1.00	29.40	70.75	4.70	4.00	16.75	55.65	87.10
		50	24.25	58.60	79.35	97.15	100.00	51.20	81.80	94.85	99.15	100.00		50	0.65	0.70	0.65	43.00	85.20	4.15	3.25	7.15	66.95	95.50
		100	46.65	88.95	98.90	100.00	100.00	78.45	97.65	100.00	100.00	100.00		100	1.00	0.45	1.00	51.25	89.45	4.25	3.40	5.95	70.20	96.20
		200	83.40	100.00	100.00	100.00	100.00	96.25	100.00	100.00	100.00	100.00		200	0.45	0.60	0.45	1.05	70.95	5.45	3.50	5.05	6.15	79.95

Table B18: Size Adjusted Power Under Homogeneous Alternative – DGP 1: No Factor Dependence, High Spatial Dependence

			Overall EPA Test												Joint EPA Test										
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size					
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S^{(1)}_{n,T}$	10	1.05	2.00	2.30	4.25	6.05	6.80	8.35	8.15	11.50	17.60	$J^{(1)}_{n,T}$	10	1.15	1.95	2.25	4.20	5.60	6.45	7.70	8.15	11.30	16.55
		20	1.55	2.05	2.95	6.40	12.50	6.90	8.90	12.80	17.60	26.70		20	2.20	1.45	2.35	5.25	11.55	7.15	8.75	11.70	15.85	26.45
		30	1.75	5.00	4.40	8.20	17.00	9.30	11.10	14.10	20.70	35.80		30	1.85	2.70	3.60	6.70	16.60	6.70	9.90	13.40	16.55	32.70
		50	3.15	5.70	8.05	17.25	32.00	10.80	16.65	21.40	34.50	55.10		50	1.50	3.00	5.95	10.80	25.00	8.60	12.10	14.90	25.15	43.80
		100	5.45	15.50	26.15	43.70	77.15	16.85	32.60	45.10	66.75	89.90		100	2.35	3.95	6.55	18.80	40.35	8.45	13.50	20.35	32.95	65.85
		200	11.40	27.35	46.40	69.80	95.85	24.65	51.05	70.05	87.60	99.00		200	3.15	7.85	14.00	30.20	72.50	10.20	20.65	30.00	48.95	85.75
Truncated	$S^{(2)}_{n,T}$	10	1.55	1.95	2.35	4.10	6.10	6.70	8.25	8.15	11.40	17.70	$J^{(2)}_{n,T}$	10	0.75	1.40	1.75	4.25	4.85	4.90	7.15	9.10	10.90	14.90
		20	2.40	1.75	2.15	6.70	11.40	7.10	9.15	13.10	17.60	27.40		20	0.30	0.55	0.55	0.75	0.30	2.50	2.70	3.35	3.50	4.40
		30	2.20	4.05	3.75	7.45	17.15	9.35	10.60	14.45	21.15	36.15		30	0.60	0.35	0.40	0.90	0.35	2.00	2.70	2.65	3.55	2.85
		50	3.30	6.45	8.90	17.40	33.90	11.10	16.05	23.00	33.60	56.10		50	0.55	0.65	0.60	0.15	0.10	2.85	2.05	3.00	2.15	3.00
		100	6.15	15.35	26.50	42.65	76.75	17.25	32.00	45.15	66.00	90.05		100	0.65	0.30	0.50	0.80	0.30	2.60	2.65	3.10	2.75	1.75
		200	10.45	25.25	46.40	70.70	95.80	24.15	52.10	70.00	87.70	99.10		200	0.45	0.60	0.85	0.65	0.85	2.40	2.80	2.50	2.45	3.25
Bartlett	$S^{(2)}_{n,T}$	10	1.05	2.00	2.30	4.25	6.05	6.80	8.35	8.15	11.50	17.60	$J^{(2)}_{n,T}$	10	1.15	1.95	2.25	4.20	5.60	6.45	7.70	8.15	11.30	16.55
		20	1.85	2.00	2.30	6.50	11.90	6.85	8.85	12.75	17.75	27.05		20	1.55	1.60	2.20	5.25	11.55	6.30	8.00	11.30	16.25	25.80
		30	2.05	4.60	3.90	7.70	16.95	8.50	11.40	14.70	20.75	36.40		30	1.25	2.20	2.90	5.60	13.75	6.25	8.45	10.80	15.95	29.75
		50	3.30	6.40	8.45	17.75	33.35	10.80	16.60	22.90	34.25	55.30		50	1.20	2.30	5.50	8.50	21.70	6.60	9.60	14.00	22.35	40.50
		100	5.70	14.90	26.40	42.65	76.50	17.25	32.15	45.35	66.70	89.85		100	1.35	2.75	4.30	13.20	31.90	7.15	10.25	14.95	24.85	51.70
		200	10.40	25.60	45.70	69.90	95.80	24.55	51.75	70.35	88.10	99.00		200	1.15	4.10	6.50	16.15	52.75	7.25	11.35	18.55	32.30	70.60
Parzen	$S^{(2)}_{n,T}$	10	1.05	2.00	2.30	4.25	6.05	6.80	8.35	8.15	11.50	17.60	$J^{(2)}_{n,T}$	10	1.15	1.95	2.25	4.20	5.60	6.45	7.70	8.15	11.30	16.55
		20	1.50	1.85	2.35	6.45	12.25	6.70	8.55	12.80	17.75	27.00		20	1.65	1.45	2.05	5.05	11.80	6.90	7.75	11.75	15.45	25.90
		30	2.00	5.10	3.95	7.95	16.80	8.70	11.30	14.45	20.90	36.25		30	1.80	1.95	3.35	6.35	15.15	6.65	9.85	12.55	16.10	32.00
		50	3.25	6.35	8.20	17.70	32.55	10.95	16.80	22.60	34.75	55.40		50	1.35	2.70	5.95	10.30	23.10	7.05	10.35	14.10	23.95	42.55
		100	5.40	15.10	26.10	42.70	76.80	17.00	32.20	45.30	66.75	89.85		100	1.75	3.75	5.15	16.75	35.90	7.55	11.25	17.25	27.85	59.40
		200	10.80	25.10	45.85	69.50	95.80	24.20	51.55	70.10	87.90	99.05		200	1.45	5.20	10.00	21.75	64.55	7.45	15.95	24.95	39.75	80.15
Tukey	$S^{(2)}_{n,T}$	10	1.05	2.00	2.30	4.25	6.05	6.80	8.35	8.15	11.50	17.60	$J^{(2)}_{n,T}$	10	1.15	1.95	2.25	4.20	5.60	6.45	7.70	8.15	11.30	16.55
		20	1.75	2.05	2.30	6.50	12.00	6.90	8.80	12.70	17.75	27.00		20	1.15	1.65	1.80	5.45	11.70	5.85	6.95	11.25	15.35	25.05
		30	2.05	4.70	4.00	7.70	16.80	8.55	11.30	14.70	20.70	36.50		30	0.70	1.80	3.05	5.30	14.10	5.90	8.60	11.00	15.95	30.20
		50	3.25	6.45	8.40	17.70	33.15	10.85	16.65	22.90	34.30	55.25		50	1.10	2.05	5.10	9.15	21.95	6.60	10.05	14.00	23.65	40.80
		100	5.65	14.95	26.35	42.60	76.75	17.15	32.20	45.40	66.75	89.85		100	0.65	2.20	3.40	10.95	24.50	5.55	9.50	14.10	22.10	48.05
		200	10.35	25.35	45.60	69.75	95.80	24.65	51.50	70.10	88.00	99.00		200	0.85	3.45	5.55	12.40	49.90	4.95	10.20	17.15	29.80	65.65
QS	$S^{(2)}_{n,T}$	10	1.20	2.00	2.25	4.20	5.95	6.75	8.15	8.05	11.50	17.90	$J^{(2)}_{n,T}$	10	1.10	1.95	2.15	4.15	5.50	6.20	7.65	8.25	11.20	16.65
		20	2.05	1.80	2.20	6.60	11.70	7.00	9.00	12.80	17.80	27.05		20	1.05	2.00	2.00	4.45	9.15	6.25	6.60	10.45	15.00	24.90
		30	2.20	4.50	3.90	7.80	17.05	8.60	11.15	14.70	20.95	36.40		30	1.10	2.30	2.90	5.25	11.25	6.25	7.95	9.00	14.20	26.45
		50	3.45	6.40	8.45	17.70	33.35	11.00	16.60	23.05	34.20	55.40		50	1.35	2.10	4.25	7.35	19.90	5.95	7.65	12.90	19.80	34.15
		100	5.80	14.80	26.45	42.60	76.65	17.10	32.30	45.35	66.65	89.85		100	1.25	1.85	2.60	7.50	15.25	6.00	8.15	10.95	15.95	39.50
		200	10.35	26.20	45.85	69.80	95.80	24.35	51.75	70.15	87.85	99.00		200	1.20	2.15	2.75	7.75	31.05	5.55	7.85	12.10	20.95	49.90
	$S^{(3)}_{n,T}$	10	1.30	1.70	2.20	4.00	5.70	6.60	7.85	8.55	11.25	16.95	$J^{(3)}_{n,T}$	10		1.15	1.05	1.50	2.00		5.40	5.85	5.65	8.70
		20	1.70	2.00	2.40	6.75	10.20	7.20	9.00	12.95	17.55	28.10		20			1.15	1.25	2.30			5.55	5.85	7.45
		30	1.75	3.30	3.60	6.20	17.65	8.95	11.20	15.25	20.80	36.80		30				1.30	1.80				6.45	8.15
		50	2.55	4.80	9.80	16.45	28.85	10.85	15.10	23.15	32.45	54.60		50					2.00					8.40
		100	4.40	11.50	19.50	41.40	75.30	16.75	28.95	42.55	63.55	89.95		100										
		200	7.60	22.75	42.30	62.75	95.00	23.15	47.75	65.95	86.45	98.95		200										
Fixed	$S^{(4)}_{n,T}$	10	1.30	1.65	2.20	3.95	5.75	6.75	7.70	8.50	11.20	17.00	$J^{(4)}_{n,T}$	10	1.05	0.90	1.15	1.05	1.60	5.15	4.65	4.75	5.00	6.90
		20	1.50	2.00	2.40	6.75	10.45	7.60	9.30	12.65	17.85	27.80		20	0.85	0.75	0.70	1.10	1.10	4.75	4.80	4.75	5.15	5.60
		30	1.70	2.50	3.55	6.40	17.45	8.45	10.85	14.00	20.25	36.60		30	0.55	1.05	1.05	0.90	1.05	4.00	4.50	4.75	5.30	5.15
		50	2.25	4.00	6.95	14.50	28.10	9.10	14.55	21.95	31.70	54.35		50	1.15	1.05	1.75	1.90	1.65	4.60	4.90	6.45	5.50	5.45
		100	2.85	4.10	7.00	11.60	44.55	10.15	21.70	29.85	44.40	81.45		100	0.90	1.35	2.50	4.05	10.70	4.85	6.00	9.90	13.10	23.60
		200	3.25	7.80	13.05	22.20	62.80	12.15	27.20	41.90	72.30	95.50		200	1.05	2.10	3.15	5.55	15.65	4.50	6.90	7.95	14.05	28.50
Expanding	$S^{(4)}_{n,T}$	10	1.95	1.65	2.20	4.20	6.05	6.15	7.70	8.60	11.35	17.15	$J^{(4)}_{n,T}$	10	0.85	1.10	0.75	1.05	0.85	4.70	4.05	4.55	4.55	5.25
		20	1.50	2.00	2.40	6.75	10.45	7.60	9.30	12.65	17.85	27.80		20	0.85	0.75	0.70	1.10	1.10	4.75	4.80	4.75	5.15	5.60
		30	1.70	2.50	3.55	6.40	17.45	8.45	10.85	14.00	20.25	36.60		30	0.55	1.05	1.05	0.90	1.05	4.00	4.50	4.75	5.30	5.15
		50	2.25	4.00	6.95	14.50	28.10	9.10	14.55	21.95	31.70	54.35		50	1.15	1.05	1.75	1.90	1.65	4.60	4.90	6.45	5.50	5.45
		100	1.70	3.85	7.85	21.00	58.95	13.10	22.65	36.50	55.75	85.15		100	0.80	1.00	1.40	2.50	5.90	4.50	4.45	7.35	8.75	16.55
		200	2.00	7.85	19.35	43.00	79.25	14.35	36.10	52.95	79.65	97.20		200	0.55	1.25	1.70	2.75	7.95	3.25	4.70	6.20	8.65	17.55
Fixed	$S^{(5)}_{n,T}$	10	1.30	1.65	2.20	3.95	5.90	6.50	7.65	8.50	11.20	17.00	$J^{(5)}_{n,T}$	10	0.25	0.85	0.65	1.15	1.20	3.10	3.85	4.80	5.60	6.85
		20	1.40	1.80	2.50	6.70	10.15	7.20	9.40	12.95	17.65	27.60		20	0.80	0.60	1.05	0.95	0.60	3.45	3.15	3.55	3.25	4.65
		30	1.65	3.35	3.90	6.35	18.35	9.25	11.10	14.05	20.45	37.00		30	0.45	0.45	0.50	0.95	0.80	3.20	2.70	3.25	3.35	3.60
		50	2.75	4.55	8.50	16.40	29.75	9.90	15.70	23.35	33.10	54.90		50	0.40	0.70	0.55	0.45	0.25	2.75	3.50	3.20	2.35	2.95
		100	4.50	9.50	16.75	32.60	72.20	15.05	30.35	42.15	60.65	88.70		100	0.50	0.80	0.30	0.55	0.40	3.20	3.70	2.40	2.85	2.35
		200	6.50	18.30	37.25	60.60	91.85	21.05	45.30	64.00	85.15	98.90		200	0.10	0.45	0.30	0.75	0.65	2.85	2.15	2.90	2.95	3.35
Expanding	$S^{(5)}_{n,T}$	10	1.85	1.95	2.45	4.35	6.25	6.75	7.95	8.55	11.55	17.65	$J^{(5)}_{n,T}$	10	0.65	0.50	0.85	0.90	0.35	4.00	5.75	5.40	5.60	6.50
		20	1.45	1.90	2.60	6.80	10.40	7.60	9.50	13.20	17.80	28.00		20	0.70	0.90	0.90	0.40	1.05	3.50	4.55	4.15	3.35	6.80
		30	1.80	3.50	4.15	6.60	18.70	9.65	11.60	14.65	20.85	37.50		30	0.65	0.45	0.50	1.05	0.30	3.05	3.55	4.15	4.25	3.50
		50	3.35	5.20	9.15	17.55	30.85	10.95	16.40	24.25	34.00	55.95		50	0.75	1.15	0.45	0.65	0.25	4.10	4.30	3.30	3.15	3.40
		100	4.60	12.10	20.60	40.50	73.55	18.20	30.20	43.95	64.10	90.00		100	0.45	0.55	0.60	0.80	0.75	4.50	2.85	3.95	3.50	2.95
		200	6.90	22.25	37.40	62.00	93.90	21.75	48.60	64.55	86.90	98.90		200	0.55	1.20	0.30	0.60	0.55	3.20	3.80	2.50	2.90	2.85

Table B19: Size Adjusted Power Under Homogeneous Alternative – DGP 2: Factor Dependence, No Spatial Dependence

			Overall EPA Test												Joint EPA Test										
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	44.80	81.20	95.85	99.85	100.00	71.85	94.70	99.15	99.95	100.00	$J_{n,T}^{(1)}$	10	44.60	87.05	97.80	99.85	100.00	74.90	96.95	99.70	100.00	100.00
		20	51.15	87.85	97.15	99.90	100.00	72.45	96.35	99.30	100.00	100.00		20	51.95	92.85	99.00	100.00	100.00	76.40	98.35	99.75	100.00	100.00
		30	49.50	87.75	97.70	99.95	100.00	74.15	95.95	99.60	100.00	100.00		30	48.85	93.30	99.30	100.00	100.00	78.45	98.45	99.95	100.00	100.00
		50	43.85	86.00	98.10	100.00	100.00	73.20	95.65	99.55	100.00	100.00		50	45.70	93.10	99.45	100.00	100.00	79.00	98.35	99.95	100.00	100.00
		100	48.90	82.20	97.20	99.95	100.00	73.65	95.05	99.25	100.00	100.00		100	50.35	87.55	98.95	100.00	100.00	79.35	98.40	99.85	100.00	100.00
		200	51.55	87.50	98.30	99.95	100.00	72.60	96.10	99.65	100.00	100.00		200	52.75	92.25	99.75	100.00	100.00	78.25	98.55	99.95	100.00	100.00
Truncated	$S_{n,T}^{(2)}$	10	40.30	76.55	94.65	99.70	100.00	67.20	93.45	98.85	99.95	100.00	$J_{n,T}^{(2)}$	10	1.95	13.50	17.20	18.25	94.20	35.15	73.00	91.15	96.20	98.05
		20	38.50	84.10	95.75	99.80	100.00	66.25	94.90	99.30	100.00	100.00		20	2.85	2.20	3.30	3.25	21.90	15.65	27.95	44.45	75.30	89.20
		30	39.40	84.50	97.05	99.95	100.00	68.05	94.95	99.35	100.00	100.00		30	1.20	2.25	4.35	6.05	8.20	12.25	20.70	27.40	61.60	79.20
		50	33.95	80.65	97.30	100.00	100.00	68.70	95.00	99.40	100.00	100.00		50	1.70	1.70	4.00	4.75	6.85	11.80	15.85	41.50	64.80	80.10
		100	38.50	75.70	95.90	99.85	100.00	67.05	93.70	99.15	100.00	100.00		100	2.05	1.85	2.70	3.90	29.25	12.70	29.80	44.25	71.40	81.40
		200	38.35	81.85	97.80	99.90	100.00	66.70	94.85	99.55	100.00	100.00		200	2.55	2.35	2.60	5.90	9.20	11.10	19.15	23.85	47.55	68.90
Bartlett	$S_{n,T}^{(2)}$	10	44.80	81.20	95.85	99.85	100.00	71.85	94.70	99.15	99.95	100.00	$J_{n,T}^{(2)}$	10	44.60	87.05	97.80	99.85	100.00	74.90	96.95	99.70	100.00	100.00
		20	44.05	85.80	96.25	99.85	100.00	68.60	95.40	99.30	100.00	100.00		20	49.55	94.60	99.50	100.00	100.00	75.60	99.15	100.00	100.00	100.00
		30	42.70	84.85	96.95	99.95	100.00	69.85	95.40	99.45	100.00	100.00		30	48.80	95.80	99.75	100.00	100.00	79.10	99.45	100.00	100.00	100.00
		50	38.00	83.80	97.45	100.00	100.00	71.30	95.40	99.45	100.00	100.00		50	45.45	95.60	100.00	100.00	100.00	83.15	99.65	100.00	100.00	100.00
		100	40.10	77.15	96.35	99.85	100.00	68.70	93.95	99.20	100.00	100.00		100	49.60	96.75	100.00	100.00	100.00	86.85	100.00	100.00	100.00	100.00
		200	40.95	82.60	98.00	99.90	100.00	67.95	95.05	99.55	100.00	100.00		200	56.25	99.75	100.00	100.00	100.00	90.10	100.00	100.00	100.00	100.00
Parzen	$S_{n,T}^{(2)}$	10	44.80	81.20	95.85	99.85	100.00	71.85	94.70	99.15	99.95	100.00	$J_{n,T}^{(2)}$	10	44.60	87.05	97.80	99.85	100.00	74.90	96.95	99.70	100.00	100.00
		20	45.80	87.35	97.00	99.85	100.00	70.25	95.85	99.30	100.00	100.00		20	51.60	93.45	99.35	100.00	100.00	75.25	98.55	99.90	100.00	100.00
		30	46.50	86.35	96.95	99.95	100.00	71.40	95.50	99.50	100.00	100.00		30	49.90	94.25	99.45	100.00	100.00	78.75	98.80	100.00	100.00	100.00
		50	40.85	85.30	97.65	100.00	100.00	72.05	95.50	99.45	100.00	100.00		50	46.30	93.90	99.80	100.00	100.00	79.45	98.95	100.00	100.00	100.00
		100	42.80	78.90	96.50	99.85	100.00	70.30	94.15	99.20	100.00	100.00		100	50.25	92.95	99.80	100.00	100.00	82.85	99.70	100.00	100.00	100.00
		200	42.70	83.95	97.95	99.90	100.00	68.35	95.35	99.65	100.00	100.00		200	51.15	98.20	100.00	100.00	100.00	84.70	99.95	100.00	100.00	100.00
Tukey	$S_{n,T}^{(2)}$	10	44.80	81.20	95.85	99.85	100.00	71.85	94.70	99.15	99.95	100.00	$J_{n,T}^{(2)}$	10	44.60	87.05	97.80	99.85	100.00	74.90	96.95	99.70	100.00	100.00
		20	44.10	86.55	96.35	99.85	100.00	68.85	95.50	99.30	100.00	100.00		20	49.60	95.25	99.50	100.00	100.00	76.40	99.05	100.00	100.00	100.00
		30	43.25	85.00	96.95	99.95	100.00	70.45	95.50	99.45	100.00	100.00		30	48.20	95.90	99.70	100.00	100.00	79.00	99.30	100.00	100.00	100.00
		50	38.55	83.90	97.45	100.00	100.00	71.45	95.35	99.45	100.00	100.00		50	41.30	95.60	100.00	100.00	100.00	82.05	99.65	100.00	100.00	100.00
		100	40.00	77.20	96.35	99.85	100.00	68.80	93.95	99.20	100.00	100.00		100	47.85	98.30	100.00	100.00	100.00	87.40	100.00	100.00	100.00	100.00
		200	41.10	82.75	98.00	99.90	100.00	67.90	95.05	99.55	100.00	100.00		200	4.75	100.00	100.00	100.00	100.00	77.65	100.00	100.00	100.00	100.00
QS	$S_{n,T}^{(2)}$	10	43.95	80.30	95.80	99.80	100.00	70.95	94.45	99.10	99.95	100.00	$J_{n,T}^{(2)}$	10	43.55	86.55	97.75	99.90	100.00	74.10	96.85	99.70	100.00	100.00
		20	41.85	84.20	96.10	99.85	100.00	67.75	95.15	99.35	100.00	100.00		20	48.65	95.60	99.65	100.00	100.00	75.45	99.15	100.00	100.00	100.00
		30	42.05	84.70	96.95	99.95	100.00	69.25	95.20	99.40	100.00	100.00		30	51.30	97.30	99.95	100.00	100.00	79.80	99.70	100.00	100.00	100.00
		50	36.25	83.50	97.45	100.00	100.00	70.60	95.25	99.45	100.00	100.00		50	43.75	97.85	100.00	100.00	100.00	86.35	100.00	100.00	100.00	100.00
		100	39.35	76.50	96.05	99.85	100.00	67.85	93.85	99.20	100.00	100.00		100	58.40	99.35	100.00	100.00	100.00	90.95	100.00	100.00	100.00	100.00
		200	40.30	82.30	97.90	99.90	100.00	67.40	94.90	99.55	100.00	100.00		200	68.25	100.00	100.00	100.00	100.00	96.00	100.00	100.00	100.00	100.00
	$S_{n,T}^{(3)}$	10	37.85	72.25	94.65	99.70	100.00	65.75	92.80	98.75	99.95	100.00	$J_{n,T}^{(3)}$	10		40.15	87.50	99.45	100.00		72.15	97.95	99.95	100.00
		20	34.85	83.55	95.70	99.80	100.00	65.50	94.80	99.15	100.00	100.00		20			75.80	100.00	100.00			90.00	100.00	100.00
		30	34.05	83.70	96.70	99.95	100.00	67.55	94.85	99.35	100.00	100.00		30				99.75	100.00				100.00	100.00
		50	31.70	80.15	97.25	99.95	100.00	67.10	95.00	99.40	100.00	100.00		50					100.00					100.00
		100	37.15	74.40	95.70	99.85	100.00	65.65	93.55	99.15	100.00	100.00		100										
		200	36.05	81.30	97.70	99.85	100.00	66.50	94.80	99.55	100.00	100.00		200										
Fixed	$S_{n,T}^{(4)}$	10	38.40	73.40	94.80	99.70	100.00	66.35	92.95	98.80	99.95	100.00	$J_{n,T}^{(4)}$	10	1.10	9.80	42.15	97.55	100.00	4.15	31.75	85.65	99.60	100.00
		20	35.50	83.85	95.70	99.80	100.00	65.85	94.80	99.25	100.00	100.00		20	1.80	15.15	53.25	99.05	100.00	4.25	30.40	75.25	99.95	100.00
		30	34.85	83.70	96.70	99.95	100.00	67.75	94.85	99.35	100.00	100.00		30	2.50	17.90	55.20	96.80	100.00	6.10	32.35	75.45	99.70	100.00
		50	32.00	80.45	97.30	99.95	100.00	67.15	95.10	99.40	100.00	100.00		50	3.20	25.15	59.35	97.75	100.00	7.00	35.95	74.20	98.95	100.00
		100	37.30	74.65	95.75	99.85	100.00	65.70	93.55	99.15	100.00	100.00		100	5.00	32.70	67.65	98.00	100.00	7.15	41.25	74.70	98.80	100.00
		200	36.30	81.35	97.70	99.85	100.00	66.50	94.85	99.55	100.00	100.00		200	6.10	35.85	70.80	98.55	100.00	8.90	41.80	75.40	99.30	100.00
Expanding	$S_{n,T}^{(4)}$	10	38.65	73.65	94.90	99.70	100.00	66.60	93.00	98.85	99.95	100.00	$J_{n,T}^{(4)}$	10	3.25	16.80	55.30	97.60	100.00	11.90	49.85	90.80	99.65	100.00
		20	35.50	83.85	95.70	99.80	100.00	65.85	94.80	99.25	100.00	100.00		20	1.80	15.15	53.25	99.05	100.00	4.25	30.40	75.25	99.95	100.00
		30	34.85	83.70	96.70	99.95	100.00	67.75	94.85	99.35	100.00	100.00		30	2.50	17.90	55.20	96.80	100.00	6.10	32.35	75.45	99.70	100.00
		50	32.00	80.45	97.30	99.95	100.00	67.15	95.10	99.40	100.00	100.00		50	3.20	25.15	59.35	97.75	100.00	7.00	35.95	74.20	98.95	100.00
		100	37.25	74.65	95.75	99.85	100.00	65.70	93.55	99.15	100.00	100.00		100	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		200	36.25	81.30	97.70	99.85	100.00	66.50	94.80	99.55	100.00	100.00		200	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fixed	$S_{n,T}^{(5)}$	10	38.70	73.55	94.80	99.70	100.00	66.25	93.05	98.80	99.95	100.00	$J_{n,T}^{(5)}$	10	0.25	3.20	44.00	97.85	100.00	1.85	29.65	88.00	99.65	100.00
		20	35.30	83.85	95.65	99.85	100.00	65.60	94.80	99.20	100.00	100.00		20	0.45	0.35	1.05	99.05	100.00	2.10	2.60	34.45	100.00	100.00
		30	34.95	83.65	96.65	99.95	100.00	67.75	94.85	99.30	100.00	100.00		30	0.10	0.05	0.60	95.30	100.00	1.30	1.50	6.45	99.65	100.00
		50	31.90	80.40	97.30	99.95	100.00	67.10	95.05	99.40	100.00	100.00		50	0.30	0.25	0.75	91.95	100.00	1.15	1.60	4.60	96.70	100.00
		100	37.30	74.60	95.75	99.85	100.00	65.70	93.55	99.15	100.00	100.00		100	0.30	0.35	0.60	82.65	99.95	1.25	1.80	3.45	90.55	100.00
		200	36.30	81.35	97.70	99.85	100.00	66.50	94.85	99.55	100.00	100.00		200	0.05	0.10	0.35	0.15	99.90	0.95	1.30	1.65	2.70	99.90
Expanding	$S_{n,T}^{(5)}$	10	38.20	73.05	94.80	99.70	100.00	66.45	93.10	98.80	99.95	100.00	$J_{n,T}^{(5)}$	10	1.40	18.40	58.80	97.85	100.00	17.40	62.20	92.60	99.35	100.00
		20	35.50	83.90	95.65	99.85	100.00	65.70	94.80	99.25	100.00	100.00		20	2.10	1.50	28.55	99.85	100.00	9.85	19.85	86.40	100.00	100.00
		30	35.05	83.70	96.75	99.95	100.00	67.80	94.85	99.35	100.00	100.00		30	0.85	1.60	8.05	99.55	100.00	6.80	12.80	68.45	99.85	100.00
		50	31.90	80.40	97.30	99.95	100.00	67.10	95.05	99.40	100.00	100.00		50	1.65	1.05	6.50	99.50	100.00	7.70	14.25	56.15	99.55	100.00
		100	37.30	74.65	95.75	99.85	100.00	65.70	93.55	99.15	100.00	100.00		100	0.70	0.30	0.20	0.00	0.00	2.85	1.40	0.60	0.00	0.00
		200	36.15	81.30	97.70	99.85	100.00	66.50	94.80	99.55	100.00	100.00		200	0.55	0.15	0.05	0.05	0.00	1.70	0.45	0.35	0.15	0.00

Table B20: Size Adjusted Power Under Homogeneous Alternative – DGP 2: Factor Dependence, High Spatial Dependence

			Overall EPA Test												Joint EPA Test									
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	27.15	66.80	90.10	98.55	100.00	54.30	83.65	96.80	99.85	100.00	$J_{n,T}^{(1)}$	10	28.10	70.65	93.05	99.35	100.00	57.75	87.75	98.65	99.95	100.00
		20	33.40	59.85	90.35	99.10	100.00	58.55	87.45	96.75	99.80	100.00		20	32.55	66.15	94.10	99.70	100.00	62.40	91.30	98.65	99.95	100.00
		30	30.00	76.90	92.00	99.70	100.00	60.05	92.70	97.30	99.90	100.00		30	26.35	82.45	95.75	99.95	100.00	60.15	95.40	98.80	100.00	100.00
		50	41.35	74.45	96.35	99.60	100.00	67.00	92.60	98.95	99.95	100.00		50	46.30	80.80	98.55	99.90	100.00	70.15	96.35	99.80	100.00	100.00
		100	50.60	84.75	97.40	99.75	100.00	74.70	95.40	99.65	100.00	100.00		100	53.95	91.40	99.40	100.00	100.00	78.90	98.25	99.90	100.00	100.00
		200	44.45	84.60	96.85	99.95	100.00	70.25	95.55	99.35	100.00	100.00		200	45.65	91.95	99.25	100.00	100.00	75.30	97.90	100.00	100.00	100.00
Truncated	$S_{n,T}^{(2)}$	10	23.70	63.65	88.75	98.30	100.00	51.15	83.00	96.65	99.80	100.00	$J_{n,T}^{(2)}$	10	32.25	74.75	94.10	99.40	100.00	58.55	90.30	98.65	99.95	100.00
		20	27.90	57.40	89.30	99.00	100.00	56.30	86.25	96.45	99.75	100.00		20	2.30	3.55	5.25	7.75	40.25	25.30	37.60	56.75	73.20	84.15
		30	25.55	75.60	90.90	99.55	100.00	55.60	92.05	97.10	99.90	100.00		30	2.60	2.95	7.20	12.95	31.75	18.50	43.25	55.20	71.10	80.65
		50	39.30	71.60	95.60	99.60	100.00	64.85	92.45	98.80	99.95	100.00		50	2.40	3.55	5.25	7.50	62.95	25.90	52.15	74.25	82.30	88.90
		100	48.05	84.00	97.25	99.80	100.00	72.25	94.95	99.60	100.00	100.00		100	1.85	5.80	14.15	30.65	59.55	32.80	70.55	79.00	84.25	88.50
		200	39.55	83.10	96.60	99.90	100.00	66.60	95.20	99.35	100.00	100.00		200	1.55	4.45	4.35	12.05	28.50	15.60	25.05	38.10	51.65	59.75
Bartlett	$S_{n,T}^{(2)}$	10	27.15	66.80	90.10	98.55	100.00	54.30	83.65	96.80	99.85	100.00	$J_{n,T}^{(2)}$	10	28.10	70.65	93.05	99.35	100.00	57.75	87.75	98.65	99.95	100.00
		20	30.35	58.65	89.80	99.10	100.00	57.15	86.80	96.50	99.75	100.00		20	32.15	75.80	97.15	99.95	100.00	64.35	95.60	99.60	100.00	100.00
		30	25.95	75.05	91.30	99.65	100.00	57.20	92.25	97.20	99.90	100.00		30	27.70	89.55	99.05	100.00	100.00	66.15	98.25	99.80	100.00	100.00
		50	39.65	72.25	95.80	99.60	100.00	65.45	92.80	98.95	99.95	100.00		50	47.40	89.10	99.85	100.00	100.00	77.70	99.70	100.00	100.00	100.00
		100	48.85	83.95	97.30	99.75	100.00	73.10	95.00	99.60	100.00	100.00		100	42.00	98.05	99.45	99.75	100.00	86.55	99.00	99.50	99.75	100.00
		200	40.65	83.60	96.70	99.95	100.00	67.60	95.25	99.35	100.00	100.00		200	7.75	94.75	98.75	99.85	100.00	77.85	98.75	99.05	99.85	100.00
Parzen	$S_{n,T}^{(2)}$	10	27.15	66.80	90.10	98.55	100.00	54.30	83.65	96.80	99.85	100.00	$J_{n,T}^{(2)}$	10	28.10	70.65	93.05	99.35	100.00	57.75	87.75	98.65	99.95	100.00
		20	31.20	59.85	89.90	99.10	100.00	58.05	87.15	96.60	99.75	100.00		20	30.35	69.15	95.15	99.85	100.00	62.05	92.30	98.90	100.00	100.00
		30	26.45	75.30	91.60	99.65	100.00	58.15	92.65	97.30	99.90	100.00		30	26.15	85.30	97.05	99.95	100.00	62.70	96.70	99.50	100.00	100.00
		50	40.20	73.30	96.15	99.60	100.00	65.50	92.75	98.95	99.95	100.00		50	41.40	82.50	99.10	100.00	100.00	70.40	97.75	100.00	100.00	100.00
		100	49.35	83.95	97.30	99.75	100.00	73.65	95.20	99.55	100.00	100.00		100	60.05	99.00	100.00	100.00	100.00	89.15	99.90	100.00	100.00	100.00
		200	41.70	83.65	96.70	99.95	100.00	68.70	95.40	99.35	100.00	100.00		200	50.35	99.50	100.00	100.00	100.00	90.45	100.00	100.00	100.00	100.00
Tukey	$S_{n,T}^{(2)}$	10	27.15	66.80	90.10	98.55	100.00	54.30	83.65	96.80	99.85	100.00	$J_{n,T}^{(2)}$	10	28.10	70.65	93.05	99.35	100.00	57.75	87.75	98.65	99.95	100.00
		20	30.40	58.80	89.85	99.10	100.00	57.30	86.80	96.50	99.75	100.00		20	15.75	16.45	43.20	78.85	93.15	50.40	81.15	91.30	93.70	94.95
		30	25.95	75.10	91.30	99.65	100.00	57.50	92.30	97.20	99.90	100.00		30	13.05	62.20	85.50	94.45	96.80	56.30	91.90	95.25	97.05	97.35
		50	39.75	72.70	95.90	99.60	100.00	65.40	92.80	98.95	99.95	100.00		50	12.80	52.75	85.30	82.00	95.65	59.55	88.90	95.15	96.10	96.65
		100	48.95	83.90	97.30	99.75	100.00	73.20	95.15	99.55	100.00	100.00		100	2.15	4.75	4.35	23.25	84.00	39.70	80.60	87.65	91.95	94.15
		200	40.70	83.55	96.70	99.95	100.00	68.00	95.30	99.35	100.00	100.00		200	2.60	4.25	4.40	15.55	82.90	22.45	56.70	81.65	91.30	93.40
QS	$S_{n,T}^{(2)}$	10	26.05	65.80	89.25	98.65	100.00	53.85	83.50	96.70	99.85	100.00	$J_{n,T}^{(2)}$	10	27.55	69.40	93.20	99.35	100.00	57.40	88.35	98.65	99.95	100.00
		20	30.15	58.15	89.70	99.10	100.00	57.00	86.70	96.50	99.75	100.00		20	41.55	85.30	99.10	100.00	100.00	73.55	98.90	99.95	100.00	100.00
		30	25.45	75.05	91.20	99.65	100.00	57.05	92.15	97.20	99.90	100.00		30	36.05	95.80	99.80	100.00	100.00	75.60	99.40	99.95	100.00	100.00
		50	39.40	72.10	95.80	99.60	100.00	65.30	92.80	98.95	99.95	100.00		50	52.30	97.45	100.00	100.00	100.00	85.80	99.95	100.00	100.00	100.00
		100	48.80	84.05	97.30	99.75	100.00	73.00	95.00	99.60	100.00	100.00		100	75.20	100.00	100.00	100.00	100.00	98.85	100.00	100.00	100.00	100.00
		200	40.60	83.40	96.70	99.95	100.00	67.50	95.20	99.35	100.00	100.00		200	74.20	100.00	100.00	100.00	100.00	99.05	100.00	100.00	100.00	100.00
	$S_{n,T}^{(3)}$	10	21.60	60.85	89.20	98.35	100.00	50.40	82.95	96.70	99.75	100.00	$J_{n,T}^{(3)}$	10		42.20	94.45	99.95	100.00		78.80	99.10	100.00	100.00
		20	27.35	58.05	88.45	98.95	100.00	54.20	85.75	96.30	99.80	100.00		20			55.95	99.95	100.00			85.85	100.00	100.00
		30	20.35	74.40	90.50	99.45	100.00	53.15	91.90	96.95	99.90	100.00		30				99.35	100.00				100.00	100.00
		50	33.30	69.90	94.55	99.60	100.00	62.00	91.80	98.65	99.95	100.00		50					100.00					100.00
		100	40.60	80.25	96.55	99.80	100.00	67.50	94.25	99.20	100.00	100.00		100										
		200	31.70	80.00	95.50	99.85	100.00	62.95	94.75	99.35	100.00	100.00		200										
Fixed	$S_{n,T}^{(4)}$	10	21.55	61.05	89.15	98.30	100.00	50.40	83.00	96.80	99.75	100.00	$J_{n,T}^{(4)}$	10	1.80	10.85	38.05	96.10	99.95	8.80	41.15	84.05	99.90	100.00
		20	27.45	57.85	88.45	98.95	100.00	54.45	85.80	96.30	99.80	100.00		20	1.55	13.80	34.05	79.10	100.00	6.85	31.20	66.80	98.60	100.00
		30	20.55	74.45	90.60	99.45	100.00	53.10	92.00	96.95	99.90	100.00		30	1.15	8.45	26.10	80.00	100.00	6.25	28.10	59.20	96.50	100.00
		50	33.35	69.90	94.60	99.60	100.00	61.90	91.80	98.65	99.95	100.00		50	2.75	10.55	23.20	80.80	100.00	7.50	25.50	60.50	96.30	100.00
		100	40.75	80.30	96.55	99.80	100.00	67.45	94.35	99.20	100.00	100.00		100	1.20	8.95	28.65	76.80	100.00	4.45	20.55	50.90	91.85	100.00
		200	31.75	80.00	95.50	99.85	100.00	62.95	94.80	99.35	100.00	100.00		200	2.30	16.10	27.00	82.00	100.00	6.10	24.75	53.95	93.30	100.00
Expanding	$S_{n,T}^{(4)}$	10	21.50	61.10	89.10	98.35	100.00	50.30	83.00	96.70	99.75	100.00	$J_{n,T}^{(4)}$	10	3.35	14.25	34.00	78.20	99.90	12.10	37.15	77.75	99.20	100.00
		20	27.45	57.85	88.45	98.95	100.00	54.45	85.80	96.30	99.80	100.00		20	1.55	13.80	34.05	79.10	100.00	6.85	31.20	66.80	98.60	100.00
		30	20.55	74.45	90.60	99.45	100.00	53.10	92.00	96.95	99.90	100.00		30	1.15	8.45	26.10	80.00	100.00	6.25	28.10	59.20	96.50	100.00
		50	33.35	69.90	94.60	99.60	100.00	61.90	91.80	98.65	99.95	100.00		50	2.75	10.55	23.20	80.80	100.00	7.50	25.50	60.50	96.30	100.00
		100	40.65	80.30	96.55	99.80	100.00	67.55	94.25	99.20	100.00	100.00		100	0.35	3.30	15.15	60.80	98.65	1.70	10.75	32.55	80.40	99.60
		200	31.70	80.00	95.50	99.85	100.00	62.95	94.75	99.35	100.00	100.00		200	0.30	2.20	10.15	41.50	85.60	1.00	5.25	20.85	57.60	91.55
Fixed	$S_{n,T}^{(5)}$	10	21.50	61.05	89.10	98.25	100.00	50.30	82.95	96.65	99.75	100.00	$J_{n,T}^{(5)}$	10	0.40	0.70	1.30	2.80	6.90	3.55	6.35	20.00	70.55	91.85
		20	27.45	58.25	88.40	98.95	100.00	55.05	86.00	96.40	99.80	100.00		20	0.15	0.60	0.60	0.70	1.45	1.80	3.50	4.10	15.20	67.20
		30	20.90	74.45	90.75	99.45	100.00	53.55	92.00	97.05	99.90	100.00		30	0.30	0.25	0.30	0.70	1.90	2.05	2.75	4.10	7.05	47.15
		50	33.20	70.35	94.65	99.60	100.00	62.65	91.85	98.70	99.95	100.00		50	0.35	0.35	0.70	1.10	1.50	2.00	4.05	4.35	10.25	35.90
		100	41.15	80.80	96.65	99.80	100.00	68.00	94.40	99.25	100.00	100.00		100	0.40	0.15	0.70	0.65	3.20	1.95	2.10	5.20	14.55	43.00
		200	32.10	80.95	95.55	99.85	100.00	62.80	94.90	99.35	100.00	100.00		200	0.30	0.15	0.20	0.75	0.80	1.80	1.85	2.30	4.80	10.65
Expanding	$S_{n,T}^{(5)}$	10	21.65	61.85	89.15	98.35	100.00	50.75	83.20	96.75	99.75	100.00	$J_{n,T}^{(5)}$	10	1.80	2.55	2.25	6.35	18.90	13.95	25.55	32.90	66.95	81.40
		20	27.55	58.25	88.45	99.00	100.00	55.15	86.10	96.40	99.80	100.00		20	0.75	1.45	1.05	2.25	6.00	7.60	13.50	17.65	52.85	79.95
		30	21.05	74.55	90.80	99.45	100.00	53.70	92.00	97.05	99.90	100.00		30	0.90	2.85	1.35	4.30	6.55	10.30	15.65	15.60	28.95	67.60
		50	33.45	70.45	94.65	99.60	100.00	62.70	91.85	98.70	99.95	100.00		50	1.55	2.25	2.60	5.95	7.70	8.55	16.35	18.35	42.20	60.50
		100	40.95	80.65	96.60	99.80	100.00	68.05	94.40	99.25	100.00	100.00		100	0.85	1.00	1.25	2.55	5.95	8.25	8.80	11.35	21.80	44.05
		200	31.95	80.85	95.55	99.85	100.00	62.90	94.90	99.35	100.00	100.00		200	1.55	1.25	1.25	1.55	2.05	4.95	6.50	7.75	10.35	19.60

Table B21: Size Adjusted Power Under Heterogeneous Alternative – DGP 1: No Factor Dependence, No Spatial Dependence

			Overall EPA Test												Joint EPA Test										
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	0.95	0.90	1.30	2.05	2.25	5.90	6.05	6.15	7.60	8.20	$J_{n,T}^{(1)}$	10	1.00	1.25	1.40	2.80	6.75	5.50	7.10	7.65	9.65	20.15
		20	1.25	1.65	1.55	1.50	2.85	5.15	6.30	5.45	7.00	8.70		20	1.00	2.05	2.20	5.15	10.20	5.55	7.80	8.00	14.15	25.25
		30	0.95	0.90	1.65	1.70	3.25	5.10	5.95	6.25	6.65	9.45		30	1.50	2.35	2.55	5.40	15.60	6.40	8.30	10.30	17.05	37.35
		50	1.10	1.30	1.45	2.05	2.90	5.10	6.00	5.80	7.80	10.20		50	1.15	2.25	3.85	5.80	25.85	6.95	8.90	12.10	18.60	46.80
		100	1.10	1.60	1.15	2.00	3.25	5.45	6.15	7.10	7.25	10.70		100	1.25	2.50	4.85	11.85	41.75	7.10	11.65	16.00	30.20	68.20
		200	1.55	1.50	1.35	2.60	4.45	5.05	7.45	7.10	8.85	12.45		200	2.05	4.65	7.25	19.85	79.85	9.00	17.00	24.50	45.40	91.85
Truncated	$S_{n,T}^{(2)}$	10	1.15	1.05	1.15	1.90	2.15	5.10	5.35	5.85	7.50	8.35	$J_{n,T}^{(2)}$	10	0.45	1.20	1.40	2.35	5.85	3.35	5.90	6.60	9.95	20.75
		20	1.15	1.65	1.35	1.55	2.50	4.95	5.90	6.00	7.55	8.75		20	0.65	0.10	0.50	3.05	9.45	3.25	2.40	3.95	12.20	23.05
		30	0.85	1.00	1.65	1.80	2.95	5.30	5.65	6.55	6.80	9.45		30	0.80	0.55	0.55	2.35	13.50	2.50	2.50	4.20	12.75	33.85
		50	1.15	1.20	1.55	2.00	3.15	5.15	6.05	5.75	7.85	10.25		50	0.60	0.20	0.25	3.50	21.45	3.15	2.55	2.60	14.50	42.00
		100	1.20	1.55	0.85	1.75	3.45	5.20	6.55	6.85	7.65	10.70		100	0.50	0.60	0.55	6.95	39.05	2.80	3.45	3.20	19.50	62.05
		200	1.35	1.50	1.35	2.30	4.40	5.60	7.20	7.65	8.60	12.55		200	0.35	0.25	0.40	0.20	62.15	2.15	1.95	2.65	3.45	82.95
Bartlett	$S_{n,T}^{(2)}$	10	0.95	0.90	1.30	2.05	2.25	5.90	6.05	6.15	7.60	8.20	$J_{n,T}^{(2)}$	10	1.00	1.25	1.40	2.80	6.75	5.50	7.10	7.65	9.65	20.15
		20	1.20	1.55	1.40	1.45	2.70	4.90	6.10	5.75	7.40	8.90		20	0.95	1.80	1.75	4.60	10.35	5.60	7.20	8.00	14.35	25.65
		30	1.10	0.90	1.80	1.75	3.00	4.85	5.95	6.40	6.55	9.30		30	1.45	2.15	2.65	4.70	15.40	5.75	7.95	10.35	16.50	37.05
		50	1.20	1.25	1.55	2.00	2.95	4.85	6.00	5.70	8.05	10.45		50	1.20	2.10	4.00	5.50	26.40	6.40	8.80	10.75	17.60	47.35
		100	1.20	1.55	1.30	1.90	3.15	5.45	6.45	6.25	7.20	10.85		100	1.15	2.50	4.75	9.20	38.45	6.70	11.15	15.30	28.00	68.25
		200	1.50	1.55	1.50	2.50	4.40	5.35	7.25	7.65	8.60	12.50		200	1.60	4.30	8.15	20.40	75.70	7.25	13.80	22.15	42.25	91.65
Parzen	$S_{n,T}^{(2)}$	10	0.95	0.90	1.30	2.05	2.25	5.90	6.05	6.15	7.60	8.20	$J_{n,T}^{(2)}$	10	1.00	1.25	1.40	2.80	6.75	5.50	7.10	7.65	9.65	20.15
		20	1.05	1.55	1.50	1.50	2.80	5.30	6.45	5.60	7.15	8.85		20	1.00	2.05	1.55	4.80	10.20	5.30	7.80	8.40	14.50	25.85
		30	0.95	0.90	1.70	1.80	3.10	5.05	6.00	6.30	6.65	9.45		30	1.35	2.30	2.30	5.35	16.50	6.00	8.35	10.60	16.80	37.60
		50	1.15	1.25	1.45	2.00	2.90	5.15	6.10	5.80	7.85	10.35		50	1.25	2.00	3.90	5.40	25.75	6.55	8.50	11.85	18.15	45.85
		100	1.10	1.45	1.30	1.95	3.20	5.35	6.30	6.70	7.25	10.65		100	1.20	2.70	5.45	9.65	40.70	7.25	11.10	15.10	27.80	68.60
		200	1.50	1.55	1.35	2.55	4.45	5.05	7.30	7.35	8.65	12.60		200	1.60	4.60	9.35	20.50	78.35	7.90	14.05	23.55	43.85	91.95
Tukey	$S_{n,T}^{(2)}$	10	0.95	0.90	1.30	2.05	2.25	5.90	6.05	6.15	7.60	8.20	$J_{n,T}^{(2)}$	10	1.00	1.25	1.40	2.80	6.75	5.50	7.10	7.65	9.65	20.15
		20	1.15	1.50	1.35	1.45	2.70	5.00	6.25	5.80	7.35	8.95		20	0.90	1.90	1.70	4.65	10.45	5.65	7.40	8.15	14.40	26.20
		30	0.90	0.95	1.85	1.80	3.00	4.75	5.90	6.40	6.55	9.50		30	1.35	2.25	2.60	4.80	15.55	5.85	8.40	10.55	16.60	36.80
		50	1.20	1.25	1.55	2.00	2.95	4.80	5.90	5.80	8.10	10.45		50	1.10	2.30	3.80	5.70	25.70	6.15	9.30	10.95	17.40	47.35
		100	1.15	1.55	1.40	1.90	3.15	5.45	6.35	6.20	7.25	10.85		100	1.30	2.60	4.45	8.75	39.10	6.15	10.90	15.55	27.05	68.25
		200	1.55	1.55	1.45	2.50	4.35	5.45	7.20	7.75	8.55	12.60		200	1.70	4.00	8.45	20.35	76.35	7.50	13.85	21.45	41.95	91.65
QS	$S_{n,T}^{(2)}$	10	1.00	0.95	1.30	2.10	2.25	5.95	6.30	6.30	7.25	8.25	$J_{n,T}^{(2)}$	10	0.95	1.35	1.35	2.55	6.85	6.10	6.60	7.55	9.80	20.15
		20	1.00	1.45	1.35	1.45	2.60	4.85	6.00	5.90	7.35	8.75		20	0.95	1.35	1.90	4.35	10.05	5.35	7.05	7.65	13.90	25.25
		30	0.95	0.90	1.80	1.75	3.05	4.95	5.70	6.60	6.55	9.30		30	1.40	1.65	2.40	4.60	15.20	5.45	8.25	9.40	15.65	35.95
		50	1.20	1.25	1.60	2.00	2.90	4.95	6.05	5.65	7.75	10.55		50	1.40	2.95	3.45	5.60	25.20	5.30	9.10	10.90	18.25	46.50
		100	1.20	1.55	1.20	1.90	3.25	5.35	6.35	6.30	7.30	10.75		100	1.20	2.00	4.55	8.70	38.30	5.90	10.50	14.40	27.85	66.95
		200	1.45	1.50	1.50	2.40	4.40	5.45	7.15	7.65	8.55	12.50		200	1.65	3.00	7.30	18.75	74.95	6.50	12.50	20.15	40.20	90.50
	$S_{n,T}^{(3)}$	10	1.30	1.30	1.15	2.40	2.20	4.90	5.90	5.75	7.30	7.90	$J_{n,T}^{(3)}$	10		1.40	1.65	1.85	6.05		6.10	6.85	8.65	18.40
		20	1.15	1.20	1.40	1.75	2.85	4.95	5.70	5.65	7.30	8.40		20			1.10	2.90	6.80			6.80	10.85	21.35
		30	0.90	1.25	2.05	1.65	3.00	5.15	5.45	7.40	7.05	10.15		30				2.15	9.50				9.05	26.60
		50	1.35	0.95	1.55	1.90	3.30	5.50	5.85	5.85	7.40	10.10		50					9.20					27.35
		100	1.10	1.05	1.55	1.80	3.80	5.60	5.75	6.30	8.05	10.60		100										
		200	1.45	1.80	1.25	2.65	4.10	5.35	6.55	7.40	9.10	12.20		200										
Fixed	$S_{n,T}^{(4)}$	10	1.15	1.20	1.40	1.90	2.65	5.00	5.30	5.60	6.50	8.80	$J_{n,T}^{(4)}$	10	0.65	1.00	1.50	1.85	5.45	4.80	6.20	5.85	8.45	16.60
		20	1.15	1.50	1.45	1.70	2.10	5.15	5.85	6.20	7.40	9.35		20	1.10	1.75	1.90	3.95	7.90	4.40	6.60	7.60	11.75	23.05
		30	0.80	0.90	1.65	1.15	2.60	5.05	5.85	6.85	6.20	9.30		30	1.05	1.75	2.05	2.35	12.75	4.45	5.95	8.25	13.65	30.10
		50	1.05	1.15	1.20	2.10	2.80	4.75	5.70	6.35	7.85	10.10		50	1.40	1.90	1.90	6.40	18.60	5.55	6.80	7.70	14.80	38.85
		100	1.10	1.35	1.75	1.80	3.45	5.05	5.90	6.65	7.00	11.00		100	1.30	1.90	2.15	5.95	34.25	5.30	6.90	10.55	21.15	56.30
		200	1.30	1.75	1.60	2.65	4.50	5.50	7.25	7.55	8.70	12.10		200	0.80	2.30	3.35	11.70	50.90	4.75	8.05	13.75	25.85	72.10
Expanding	$S_{n,T}^{(4)}$	10	1.05	1.00	1.45	2.05	2.35	4.70	5.10	5.90	6.85	7.75	$J_{n,T}^{(4)}$	10	1.05	1.40	1.30	2.25	6.00	5.65	6.35	6.95	9.90	16.50
		20	1.15	1.50	1.45	1.70	2.10	5.15	5.85	6.20	7.40	9.35		20	1.10	1.75	1.90	3.95	7.90	4.40	6.60	7.60	11.75	23.05
		30	0.80	0.90	1.65	1.15	2.60	5.05	5.85	6.85	6.20	9.30		30	1.05	1.75	2.05	2.35	12.75	4.45	5.95	8.25	13.65	30.10
		50	1.05	1.15	1.20	2.10	2.80	4.75	5.70	6.35	7.85	10.10		50	1.40	1.90	1.90	6.40	18.60	5.55	6.80	7.70	14.80	38.85
		100	0.95	1.60	1.55	2.00	3.35	5.70	5.70	7.25	6.65	11.15		100	0.95	1.05	3.45	5.20	28.95	3.85	5.45	8.70	16.55	51.00
		200	1.00	1.65	1.55	2.35	4.20	5.65	7.00	7.55	8.75	12.05		200	1.00	1.05	2.90	9.05	43.10	4.15	6.55	10.85	20.40	63.25
Fixed	$S_{n,T}^{(5)}$	10	1.15	1.05	1.05	1.75	2.40	5.65	5.35	5.60	6.55	8.20	$J_{n,T}^{(5)}$	10	0.60	1.00	1.40	2.35	5.10	3.30	5.75	6.50	7.95	16.50
		20	1.15	1.40	1.60	1.70	2.45	5.30	6.00	5.70	7.80	8.75		20	0.45	0.60	0.75	2.50	6.10	3.85	2.70	5.95	11.10	21.20
		30	1.05	1.05	1.45	1.25	3.10	5.35	5.75	7.10	6.50	9.30		30	0.55	0.50	0.55	2.50	9.50	3.00	3.10	4.90	11.50	25.40
		50	1.00	1.05	1.30	2.00	3.10	4.90	6.00	6.20	7.75	9.95		50	0.25	0.35	0.35	2.65	14.00	3.00	2.90	2.40	12.05	36.70
		100	1.05	1.35	1.50	1.75	3.55	4.95	5.60	6.80	6.85	10.85		100	0.50	0.55	0.20	3.00	29.40	2.30	3.65	2.95	14.30	52.30
		200	1.45	2.00	1.30	2.30	4.10	5.40	6.80	7.70	8.40	12.00		200	1.00	0.50	0.55	0.45	38.85	3.05	3.10	3.35	3.45	62.60
Expanding	$S_{n,T}^{(5)}$	10	1.30	1.35	1.80	1.90	2.30	5.25	5.70	5.90	6.80	8.55	$J_{n,T}^{(5)}$	10	0.75	1.20	1.55	2.20	5.20	3.80	5.50	6.15	8.40	16.65
		20	1.15	1.40	1.60	1.70	2.45	5.30	6.00	5.70	7.80	8.75		20	0.45	0.60	0.75	2.50	6.10	3.85	2.70	5.95	11.10	21.20
		30	1.05	1.05	1.45	1.25	3.10	5.35	5.75	7.10	6.50	9.30		30	0.55	0.50	0.55	2.50	9.50	3.00	3.10	4.90	11.50	25.40
		50	1.00	1.05	1.30	2.00	3.10	4.90	6.00	6.20	7.75	9.95		50	0.25	0.35	0.35	2.65	14.00	3.00	2.90	2.40	12.05	36.70
		100	0.70	1.80	1.20	1.95	3.55	5.40	5.50	7.05	7.30	11.30		100	0.55	0.70	0.55	2.45	22.90	2.40	3.35	3.20	12.80	48.05
		200	1.20	1.60	1.25	2.00	4.10	5.70	6.65	8.30	8.30	12.00		200	0.35	0.30	0.50	0.50	31.80	2.35	1.75	3.75	3.05	52.70

Table B22: Size Adjusted Power Under Heterogeneous Alternative – DGP 1: No Factor Dependence, High Spatial Dependence

			Overall EPA Test												Joint EPA Test										
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	0.90	1.25	0.70	0.95	1.40	4.75	5.60	5.10	5.30	5.45	$J_{n,T}^{(1)}$	10	1.05	1.25	0.90	1.30	1.80	5.00	5.50	5.65	6.35	7.05
		20	0.90	1.00	1.00	1.20	1.00	5.05	5.15	5.85	5.20	4.80		20	1.10	1.05	1.20	1.10	1.80	5.05	5.25	5.65	6.95	8.10
		30	1.05	1.25	1.15	1.15	1.35	5.00	5.00	4.85	5.20	5.65		30	1.10	1.10	1.20	1.85	2.30	5.10	5.45	6.60	7.40	10.95
		50	1.10	1.00	1.05	1.25	1.25	4.75	5.00	4.65	4.95	5.05		50	1.00	1.35	1.45	1.80	4.20	5.85	5.80	5.95	9.05	15.35
		100	0.95	1.00	1.10	1.00	1.35	5.10	4.90	5.00	5.90	6.05		100	1.25	1.65	1.85	3.85	6.45	6.20	6.60	8.30	11.05	28.10
		200	1.15	0.95	1.10	1.05	1.30	4.95	4.95	5.25	5.30	5.75		200	1.30	1.75	2.40	4.90	17.95	6.45	9.50	12.00	15.80	45.95
Truncated	$S_{n,T}^{(2)}$	10	1.10	1.20	0.80	1.05	1.50	5.00	5.30	5.10	5.20	5.60	$J_{n,T}^{(2)}$	10	1.00	1.55	2.20	4.75	8.20	5.50	6.95	10.15	14.35	24.40
		20	0.95	0.95	0.80	1.05	1.00	4.90	5.20	5.35	5.45	5.25		20	0.40	0.35	0.85	0.95	2.15	2.60	2.40	4.45	6.50	9.35
		30	0.90	1.00	1.10	1.25	1.30	5.40	4.75	4.65	5.50	5.65		30	0.75	0.45	0.60	1.10	1.60	3.10	2.95	3.60	5.85	7.85
		50	1.05	1.10	1.15	1.20	1.45	5.05	5.10	5.15	4.85	5.20		50	0.30	0.75	0.45	0.85	0.95	2.80	3.55	3.60	4.50	6.10
		100	1.00	1.20	1.00	0.90	1.35	5.20	4.85	4.80	5.60	6.00		100	0.50	0.45	1.15	0.55	0.75	2.70	3.15	3.60	4.25	5.75
		200	1.10	1.05	1.05	1.10	1.45	4.90	5.20	5.45	5.60	5.70		200	0.10	0.55	0.70	0.35	0.90	2.40	3.55	2.70	3.75	5.75
Bartlett	$S_{n,T}^{(2)}$	10	0.90	1.25	0.70	0.95	1.40	4.75	5.60	5.10	5.30	5.45	$J_{n,T}^{(2)}$	10	1.05	1.25	0.90	1.30	1.80	5.00	5.50	5.65	6.35	7.05
		20	0.85	1.05	1.00	1.20	0.95	4.85	4.95	5.55	5.20	5.00		20	1.00	1.20	1.80	2.95	9.70	5.45	6.90	9.55	17.25	37.15
		30	1.15	0.90	1.05	1.15	1.20	4.90	5.05	5.00	5.00	5.85		30	1.30	1.45	2.25	4.15	17.35	6.00	8.05	9.85	18.45	51.30
		50	0.95	1.00	1.15	1.30	1.35	4.90	5.20	5.10	5.15	5.15		50	1.20	2.10	4.15	7.10	35.70	6.15	9.20	14.05	28.45	71.50
		100	0.95	1.05	1.15	0.90	1.35	5.10	5.05	4.80	5.85	6.00		100	1.75	6.45	17.35	62.70	99.35	9.45	22.00	44.80	82.70	99.90
		200	1.05	1.00	1.00	1.10	1.30	5.00	4.95	5.50	5.65	5.70		200	1.75	8.85	24.15	72.30	100.00	9.40	26.35	53.30	91.65	100.00
Parzen	$S_{n,T}^{(2)}$	10	0.90	1.25	0.70	0.95	1.40	4.75	5.60	5.10	5.30	5.45	$J_{n,T}^{(2)}$	10	1.05	1.25	0.90	1.30	1.80	5.00	5.50	5.65	6.35	7.05
		20	0.80	1.10	1.00	1.25	1.05	4.75	4.80	5.65	5.20	4.95		20	0.95	1.05	1.15	1.50	3.30	5.25	5.70	6.50	8.80	12.90
		30	1.05	1.00	1.10	1.20	1.30	4.90	5.05	4.95	5.30	5.75		30	1.15	1.20	1.70	2.65	3.95	5.65	6.30	7.35	10.10	19.25
		50	1.10	1.00	1.05	1.30	1.30	5.00	5.15	5.10	5.05	5.15		50	1.10	1.50	2.40	2.85	8.85	6.05	6.70	8.40	12.25	30.85
		100	0.95	1.05	1.00	0.90	1.35	5.25	5.00	4.85	5.85	6.05		100	1.85	6.05	9.30	45.20	93.75	8.30	17.85	34.25	65.25	99.45
		200	1.10	1.00	1.05	1.10	1.30	4.85	5.05	5.35	5.65	5.85		200	2.00	7.45	18.80	55.10	99.90	8.30	24.70	45.50	81.60	100.00
Tukey	$S_{n,T}^{(2)}$	10	0.90	1.25	0.70	0.95	1.40	4.75	5.60	5.10	5.30	5.45	$J_{n,T}^{(2)}$	10	1.05	1.25	0.90	1.30	1.80	5.00	5.50	5.65	6.35	7.05
		20	0.90	1.10	1.00	1.20	0.95	4.90	4.90	5.45	5.30	5.00		20	0.80	1.30	1.60	4.45	14.00	4.45	7.60	10.95	19.90	42.00
		30	1.10	0.95	1.05	1.15	1.30	4.75	5.05	5.00	5.05	5.85		30	0.75	1.60	2.30	5.10	21.90	5.85	8.45	11.00	21.75	55.80
		50	0.95	1.00	1.15	1.30	1.30	4.90	5.15	5.05	5.15	5.15		50	1.15	2.00	3.65	8.20	41.20	7.00	10.70	14.80	32.35	74.80
		100	0.95	1.00	1.15	0.90	1.35	5.10	5.00	4.80	5.85	6.05		100	0.55	12.80	38.00	88.60	100.00	8.55	36.70	69.95	95.50	100.00
		200	0.95	0.95	1.00	1.10	1.30	4.95	4.90	5.40	5.65	5.75		200	0.70	14.10	42.00	87.80	100.00	7.80	37.40	68.95	97.35	100.00
QS	$S_{n,T}^{(2)}$	10	0.90	1.25	0.75	0.90	1.40	5.20	5.50	5.20	5.30	5.55	$J_{n,T}^{(2)}$	10	0.95	1.35	1.00	1.35	1.80	4.95	5.70	5.90	6.55	7.80
		20	0.90	0.95	0.95	1.20	1.00	5.00	5.00	5.60	5.25	4.95		20	1.10	2.30	3.15	11.70	41.00	7.00	10.35	18.25	37.85	75.10
		30	1.05	0.90	1.05	1.15	1.25	4.95	4.90	4.95	5.10	5.80		30	1.30	2.80	4.40	16.95	52.25	7.20	12.70	18.00	40.10	81.70
		50	1.10	1.00	1.10	1.30	1.35	4.85	5.20	5.15	5.10	5.15		50	2.00	3.20	8.70	25.50	78.30	7.70	13.20	28.10	53.30	92.85
		100	0.95	1.05	1.10	0.90	1.30	5.05	5.05	4.80	5.90	6.00		100	2.95	18.80	49.75	93.60	100.00	12.95	43.70	76.95	97.40	100.00
		200	1.10	1.05	1.00	1.10	1.30	4.95	5.05	5.45	5.55	5.65		200	2.20	15.30	41.30	92.50	100.00	8.65	35.65	70.45	98.35	100.00
	$S_{n,T}^{(3)}$	10	1.05	1.10	1.00	1.15	1.10	4.75	5.20	5.30	5.05	5.50	$J_{n,T}^{(3)}$	10		2.90	7.60	29.80	72.00		9.80	24.45	48.05	85.30
		20	1.00	1.00	0.95	1.30	0.95	5.25	5.45	5.20	5.50	5.60		20			2.75	12.25	63.40			11.60	33.55	82.50
		30	1.10	1.15	1.20	1.15	1.50	5.00	5.00	5.35	5.35	6.05		30				7.05	63.65				27.30	84.60
		50	0.95	1.00	1.45	1.25	1.15	5.15	4.90	5.25	5.00	5.55		50					56.25					83.35
		100	0.80	1.15	0.85	1.30	1.50	5.20	4.95	4.85	5.70	6.35		100										
		200	1.10	1.05	1.05	0.85	1.30	5.20	5.00	5.25	5.50	5.85		200										
Fixed	$S_{n,T}^{(4)}$	10	1.05	1.10	0.90	1.10	1.15	4.80	5.05	5.30	5.00	5.50	$J_{n,T}^{(4)}$	10	1.55	1.95	4.20	13.35	52.15	6.45	10.75	17.75	34.25	73.15
		20	0.95	1.00	0.95	1.25	1.00	5.10	5.35	5.10	5.85	5.50		20	0.90	1.25	2.25	3.90	8.80	5.95	8.15	9.60	15.70	36.00
		30	1.15	0.95	1.20	1.15	1.50	4.80	4.55	4.95	5.15	6.00		30	1.10	1.10	1.65	2.55	7.15	5.60	6.95	7.85	13.70	25.30
		50	1.00	1.25	1.15	1.20	1.20	4.85	4.85	4.80	4.90	5.60		50	1.15	1.30	2.15	4.95	10.85	5.60	7.30	9.20	14.10	28.80
		100	1.10	1.00	0.95	0.95	1.25	4.95	5.00	4.85	4.75	5.40		100	1.20	0.95	1.85	2.90	9.75	4.95	6.35	9.65	14.55	30.05
		200	0.90	1.05	1.25	1.05	0.95	5.65	4.80	4.60	5.55	6.30		200	1.15	1.65	2.65	5.75	23.85	5.20	8.00	9.45	18.25	53.25
Expanding	$S_{n,T}^{(4)}$	10	1.00	0.75	1.00	1.15	1.50	5.10	5.25	5.55	5.05	5.50	$J_{n,T}^{(4)}$	10	1.00	1.30	1.60	2.55	5.10	5.25	6.50	7.35	9.45	21.95
		20	0.95	1.00	0.95	1.25	1.00	5.10	5.35	5.10	5.85	5.50		20	0.90	1.25	2.25	3.90	8.80	5.95	8.15	9.60	15.70	36.00
		30	1.15	0.95	1.20	1.15	1.50	4.80	4.55	4.95	5.15	6.00		30	1.10	1.10	1.65	2.55	7.15	5.60	6.95	7.85	13.70	25.30
		50	1.00	1.25	1.15	1.20	1.20	4.85	4.85	4.80	4.90	5.60		50	1.15	1.30	2.15	4.95	10.85	5.60	7.30	9.20	14.10	28.80
		100	0.85	0.95	1.00	1.15	1.35	4.90	4.80	5.20	5.45	5.25		100	0.70	1.35	2.00	3.50	11.35	5.10	5.75	9.10	14.80	36.75
		200	1.00	0.85	1.05	1.00	1.00	5.25	5.05	5.30	5.15	6.05		200	1.20	1.90	2.30	5.25	24.00	4.95	7.65	9.70	17.30	59.10
Fixed	$S_{n,T}^{(5)}$	10	1.00	1.10	0.90	1.10	1.20	4.80	5.05	5.35	5.05	5.50	$J_{n,T}^{(5)}$	10	0.40	0.55	0.80	13.05	53.90	3.20	4.25	12.50	35.35	75.10
		20	0.95	1.00	1.00	1.25	0.95	5.20	5.35	5.40	5.60	5.35		20	0.80	1.05	0.55	0.90	2.10	3.10	4.30	4.65	6.20	30.05
		30	0.90	1.20	1.20	1.15	1.50	5.20	5.05	4.85	5.20	5.95		30	0.45	0.35	0.50	1.25	1.55	3.00	3.05	3.65	5.15	11.05
		50	1.05	1.05	1.10	1.40	1.30	5.05	4.90	4.95	5.25	5.85		50	0.50	0.75	0.75	1.25	1.10	3.10	3.75	3.65	5.50	8.00
		100	0.90	0.90	0.90	1.30	1.35	5.20	5.20	5.45	5.55	5.90		100	0.55	0.70	0.85	0.75	0.70	3.55	4.45	3.30	4.25	6.80
		200	1.00	0.70	1.15	1.05	1.00	5.15	5.40	5.00	5.60	6.40		200	0.45	0.40	0.50	0.50	0.85	2.60	2.75	3.55	3.25	5.25
Expanding	$S_{n,T}^{(5)}$	10	1.00	1.10	1.00	1.15	1.40	4.75	5.05	5.35	5.05	5.60	$J_{n,T}^{(5)}$	10	0.55	0.40	1.25	3.15	3.90	4.75	7.05	9.50	14.15	20.95
		20	0.95	1.00	1.00	1.25	0.95	5.20	5.35	5.40	5.60	5.35		20	0.80	1.05	0.55	0.90	2.10	3.10	4.30	4.65	6.20	30.05
		30	0.90	1.20	1.20	1.15	1.50	5.20	5.05	4.85	5.20	5.95		30	0.45	0.35	0.50	1.25	1.55	3.00	3.05	3.65	5.15	11.05
		50	1.05	1.05	1.10	1.40	1.30	5.05	4.90	4.95	5.25	5.85		50	0.50	0.75	0.75	1.25	1.10	3.10	3.75	3.65	5.50	8.00
		100	0.90	1.10	1.00	1.20	1.25	5.10	4.85	5.35	5.35	5.90		100	0.35	0.55	0.85	0.65	1.50	3.75	3.05	3.55	4.90	6.75
		200	1.00	1.00	0.80	1.00	1.05	5.15	5.15	5.00	5.70	6.25		200	0.45	0.40	0.60	0.60	0.45	3.10	2.45	2.45	2.90	4.00

Table B23: Size Adjusted Power Under Heterogeneous Alternative – DGP 2: Factor Dependence, No Spatial Dependence

			Overall EPA Test												Joint EPA Test								
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size			
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S_{n,T}^{(1)}$	10	1.05	1.20	1.00	1.30	1.25	5.10	4.95	5.40	5.10	5.40	$J_{n,T}^{(1)}$	10	1.10	1.15	1.00	1.70	1.60	5.55	5.70	6.25	6.30	9.10
		20	0.95	1.05	0.90	0.95	0.95	5.15	5.35	5.25	4.95	5.20		20	0.90	1.10	1.25	1.20	1.65	5.20	5.90	5.85	6.05	7.80
		30	1.05	0.95	1.00	1.00	0.95	5.25	5.35	5.10	5.05	4.95		30	1.05	1.05	1.15	1.35	1.75	5.25	5.80	6.25	6.45	8.55
		50	1.05	1.00	1.10	0.90	1.05	4.85	4.95	4.75	5.20	5.25		50	1.10	1.15	1.40	1.20	2.05	5.30	5.15	5.85	6.75	7.80
		100	0.95	1.00	1.05	1.00	0.95	4.95	4.90	5.30	4.85	4.80		100	1.00	1.05	1.20	1.15	1.30	5.40	5.55	5.65	5.95	8.55
		200	0.95	1.15	0.95	1.00	1.00	4.80	4.85	4.85	4.70	4.80		200	1.00	1.10	1.25	1.25	1.50	5.30	5.55	5.80	6.40	9.40
Truncated	$S_{n,T}^{(2)}$	10	0.95	1.05	0.90	1.35	1.35	4.95	5.25	5.35	4.95	6.05	$J_{n,T}^{(2)}$	10	0.80	0.85	0.80	0.50	0.85	3.90	4.20	5.25	4.60	5.70
		20	0.95	1.10	0.95	0.95	0.95	5.00	5.10	5.35	5.20	5.30		20	0.55	0.80	0.85	0.60	1.25	3.40	3.95	3.55	4.45	7.85
		30	1.05	1.05	1.10	0.95	0.95	5.00	5.00	5.05	5.15	5.45		30	0.60	0.60	0.95	1.00	0.85	2.90	3.15	3.20	3.95	5.60
		50	1.05	1.00	1.05	1.00	0.95	5.00	4.95	4.90	5.15	5.35		50	0.55	0.50	0.55	0.85	1.05	3.05	2.95	3.65	5.40	7.20
		100	1.00	1.05	1.10	0.90	0.95	4.90	5.00	5.05	4.90	4.85		100	0.45	0.60	0.55	0.80	1.55	2.05	3.50	3.80	4.65	6.55
		200	1.00	1.05	1.00	1.00	1.00	4.80	5.10	5.10	5.05	4.95		200	0.60	0.55	0.90	0.80	1.25	2.65	3.15	3.70	5.30	6.35
Bartlett	$S_{n,T}^{(2)}$	10	1.05	1.20	1.00	1.30	1.25	5.10	4.95	5.40	5.10	5.40	$J_{n,T}^{(2)}$	10	1.10	1.15	1.00	1.70	1.60	5.55	5.70	6.25	6.30	9.10
		20	1.00	1.05	0.90	1.10	0.95	5.20	4.95	5.35	5.10	5.35		20	1.10	1.35	1.25	1.90	3.95	5.45	7.95	8.90	9.60	21.95
		30	1.05	0.85	1.00	1.10	0.90	4.80	5.50	5.00	5.15	5.40		30	1.00	1.15	1.60	1.75	3.55	5.75	6.75	8.00	12.00	31.10
		50	1.00	1.00	0.95	0.90	0.90	5.10	4.90	5.00	5.50	5.35		50	1.30	1.30	2.10	2.05	4.45	6.15	6.50	8.65	10.20	30.15
		100	0.95	1.05	1.20	0.90	0.95	4.90	5.00	5.10	4.95	4.85		100	1.15	1.30	1.70	2.25	13.10	6.00	7.60	10.15	17.00	64.30
		200	1.00	0.95	0.95	1.05	1.00	4.95	5.10	5.15	4.95	4.85		200	1.15	1.70	2.65	4.60	17.85	5.90	8.95	11.10	23.90	92.35
Parzen	$S_{n,T}^{(2)}$	10	1.05	1.20	1.00	1.30	1.25	5.10	4.95	5.40	5.10	5.40	$J_{n,T}^{(2)}$	10	1.10	1.15	1.00	1.70	1.60	5.55	5.70	6.25	6.30	9.10
		20	1.00	1.20	0.95	1.05	0.95	5.10	5.05	5.20	5.05	5.40		20	1.05	1.10	1.30	1.55	2.15	5.15	6.25	6.30	7.15	10.65
		30	1.15	0.95	1.00	1.10	0.85	5.10	5.25	5.20	5.20	5.15		30	1.10	1.15	1.35	1.35	2.10	5.45	5.90	6.45	7.90	12.75
		50	1.00	0.95	0.90	0.90	1.15	4.95	4.90	5.00	5.50	5.25		50	1.10	1.10	1.50	1.20	2.30	5.45	5.60	6.60	7.85	11.20
		100	1.00	1.00	1.15	0.90	0.95	5.15	4.85	5.15	5.00	4.90		100	1.05	1.25	1.45	1.80	4.60	5.60	6.70	7.35	11.60	27.20
		200	1.00	1.05	1.05	1.05	1.00	4.90	5.05	5.05	4.90	4.90		200	1.20	1.30	1.95	2.40	3.95	5.45	6.85	7.70	12.40	41.50
Tukey	$S_{n,T}^{(2)}$	10	1.05	1.20	1.00	1.30	1.25	5.10	4.95	5.40	5.10	5.40	$J_{n,T}^{(2)}$	10	1.10	1.15	1.00	1.70	1.60	5.55	5.70	6.25	6.30	9.10
		20	1.00	1.10	0.95	1.10	0.95	5.25	4.90	5.40	5.15	5.35		20	1.15	1.60	1.20	1.80	4.30	5.35	7.95	8.80	9.20	21.10
		30	1.10	0.90	1.00	1.10	0.90	4.85	5.75	5.00	5.10	5.40		30	0.95	1.20	1.65	1.65	3.35	5.75	6.70	8.00	11.50	29.25
		50	1.00	1.00	0.95	0.90	0.95	5.05	4.90	4.95	5.55	5.40		50	1.10	1.30	1.95	1.90	4.55	5.75	6.95	8.20	10.05	29.00
		100	0.90	1.05	1.20	0.90	0.95	4.90	5.00	5.10	4.95	4.85		100	1.10	1.30	1.85	2.55	19.05	5.60	7.85	11.05	22.40	73.90
		200	1.00	0.95	0.95	1.05	1.00	4.95	5.05	5.10	4.95	4.85		200	0.60	1.60	3.05	5.10	23.95	4.85	10.15	12.40	29.70	96.15
QS	$S_{n,T}^{(2)}$	10	1.00	1.05	1.00	1.40	1.30	5.00	4.85	5.35	5.10	5.60	$J_{n,T}^{(2)}$	10	1.05	1.25	0.85	1.70	1.65	5.50	5.75	6.10	6.45	10.40
		20	0.95	0.95	0.90	1.05	0.95	5.15	4.95	5.25	5.20	5.35		20	1.15	1.90	1.60	3.00	8.95	5.90	8.40	10.40	16.00	38.10
		30	1.05	0.85	1.00	1.05	0.90	4.85	5.25	5.15	5.05	5.35		30	1.15	1.55	1.85	3.30	10.65	5.70	7.60	11.30	18.75	51.40
		50	1.00	1.00	0.95	0.90	0.90	5.10	5.05	4.95	5.35	5.40		50	1.15	1.30	2.40	3.50	15.80	6.90	8.75	11.40	16.80	59.75
		100	0.95	1.05	1.10	0.90	0.95	4.90	4.95	5.10	5.00	4.85		100	1.25	1.70	2.45	5.45	47.30	6.20	9.50	16.20	36.70	93.20
		200	1.00	0.95	1.00	1.00	1.00	5.00	5.05	5.15	5.00	4.85		200	1.30	2.30	3.90	12.30	71.95	6.55	13.00	19.30	56.25	99.70
	$S_{n,T}^{(3)}$	10	1.25	0.95	0.95	1.35	1.30	5.20	5.20	5.40	4.85	6.20	$J_{n,T}^{(3)}$	10		1.60	4.00	8.50	27.10		8.50	14.40	21.05	54.65
		20	1.05	1.05	0.95	0.90	0.90	5.10	5.00	5.25	5.60	5.40		20			5.55	14.30	61.70			12.25	36.25	79.05
		30	1.00	1.00	1.15	0.95	0.90	5.05	4.95	5.10	5.35	5.25		30				10.85	63.90				30.40	86.60
		50	1.05	1.05	1.00	1.00	1.05	4.95	4.70	5.00	5.25	5.25		50					69.90					92.45
		100	1.00	1.05	1.05	1.00	0.90	5.10	5.15	4.95	4.85	4.85		100										
		200	0.95	1.05	1.00	1.00	1.00	4.90	5.10	4.80	5.05	5.10		200										
Fixed	$S_{n,T}^{(4)}$	10	1.20	1.00	0.95	1.45	1.30	5.20	5.20	5.50	4.90	6.00	$J_{n,T}^{(4)}$	10	1.45	2.65	4.80	8.75	28.50	6.95	10.70	15.70	24.50	58.90
		20	0.95	1.05	0.95	0.85	0.90	5.05	4.95	5.30	5.55	5.30		20	2.10	5.80	11.25	23.20	70.50	6.55	15.75	24.15	44.10	83.75
		30	0.95	0.95	1.15	0.95	0.90	5.15	4.95	5.15	5.30	5.20		30	2.50	5.35	13.45	29.25	81.60	8.15	19.35	33.00	58.75	94.50
		50	1.00	1.00	1.00	1.00	1.05	4.95	4.75	4.95	5.30	5.25		50	2.45	10.95	20.85	61.75	97.40	10.80	27.05	44.25	79.50	99.35
		100	1.00	1.05	1.05	1.00	0.90	5.10	5.10	4.95	4.90	4.85		100	4.50	19.20	46.85	87.85	100.00	11.20	40.95	64.45	95.10	100.00
		200	0.95	1.05	1.00	1.00	1.00	4.90	5.10	4.80	5.05	5.10		200	6.10	30.70	68.20	98.25	100.00	16.00	49.50	81.75	99.40	100.00
Expanding	$S_{n,T}^{(4)}$	10	1.15	1.00	0.95	1.50	1.35	5.15	5.20	5.50	4.90	5.90	$J_{n,T}^{(4)}$	10	1.80	2.10	4.85	8.60	20.55	7.80	10.45	15.40	21.35	50.30
		20	0.95	1.05	0.95	0.85	0.90	5.05	4.95	5.30	5.55	5.30		20	2.10	5.80	11.25	23.20	70.50	6.55	15.75	24.15	44.10	83.75
		30	0.95	0.95	1.15	0.95	0.90	5.15	4.95	5.15	5.30	5.20		30	2.50	5.35	13.45	29.25	81.60	8.15	19.35	33.00	58.75	94.50
		50	1.00	1.00	1.00	1.00	1.05	4.95	4.75	4.95	5.30	5.25		50	2.45	10.95	20.85	61.75	97.40	10.80	27.05	44.25	79.50	99.35
		100	1.00	1.05	1.05	1.00	0.90	5.10	5.15	4.95	4.90	4.85		100	1.55	8.35	14.65	36.35	61.10	5.60	16.75	28.50	51.60	72.90
		200	0.95	1.05	1.00	1.00	1.00	4.90	5.10	4.80	5.05	5.10		200	1.55	6.50	13.50	19.50	5.95	5.70	13.90	20.75	24.30	8.45
Fixed	$S_{n,T}^{(5)}$	10	1.30	1.00	1.00	1.45	1.30	5.20	5.20	5.45	4.95	6.20	$J_{n,T}^{(5)}$	10	0.25	1.30	4.55	8.70	25.90	2.85	9.35	13.95	22.45	56.50
		20	1.05	1.10	0.95	0.90	0.90	5.10	4.90	5.30	5.55	5.40		20	1.00	0.45	0.95	16.45	61.15	3.55	3.35	11.60	39.30	80.80
		30	0.95	0.95	1.15	0.95	0.90	5.20	4.95	5.10	5.35	5.25		30	0.30	0.55	0.75	24.95	77.80	2.85	3.30	5.80	48.10	91.75
		50	1.05	1.00	1.00	1.00	1.05	4.95	4.75	4.95	5.30	5.25		50	0.60	0.30	0.85	46.05	96.80	2.85	4.00	6.30	68.00	98.85
		100	1.00	1.05	1.05	1.00	0.90	5.10	5.15	4.95	4.85	4.85		100	0.45	0.45	0.70	70.35	99.95	3.45	2.55	5.10	86.85	100.00
		200	0.95	1.05	1.00	1.00	1.00	4.90	5.10	4.80	5.05	5.10		200	0.45	0.30	0.80	0.30	100.00	2.95	2.95	3.20	4.20	100.00
Expanding	$S_{n,T}^{(5)}$	10	1.15	1.00	0.90	1.50	1.30	5.20	5.30	5.45	5.00	6.10	$J_{n,T}^{(5)}$	10	0.15	0.90	2.45	7.80	20.20	3.05	7.40	13.35	20.75	52.20
		20	1.05	1.10	0.95	0.90	0.90	5.10	4.90	5.30	5.55	5.40		20	1.00	0.45	0.95	16.45	61.15	3.55	3.35	11.60	39.30	80.80
		30	0.95	0.95	1.15	0.95	0.90	5.20	4.95	5.10	5.35	5.25		30	0.30	0.55	0.75	24.95	77.80	2.85	3.30	5.80	48.10	91.75
		50	1.05	1.00	1.00	1.00	1.05	4.95	4.75	4.95	5.30	5.25		50	0.60	0.30	0.85	46.05	96.80	2.85	4.00	6.30	68.00	98.85
		100	1.00	1.05	1.05	1.00	0.90	5.10	5.15	4.95	4.85	4.85		100	0.85	0.45	0.65	21.35	57.70	3.95	2.60	3.05	38.30	71.25
		200	0.95	1.05	1.00	1.00	1.00	4.90	5.10	4.80	5.05	5.10		200	0.55	0.75	0.00	0.10	4.05	3.05	2.55	1.50	2.00	4.95

Table B24: Size Adjusted Power Under Heterogeneous Alternative – DGP 2: Factor Dependence, High Spatial Dependence

			Overall EPA Test												Joint EPA Test									
			1% Nominal Size					5% Nominal Size							1% Nominal Size					5% Nominal Size				
Option	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100	*Test*	$n\backslash T$	10	20	30	50	100	10	20	30	50	100
	$S^{(1)}_{n,T}$	10	1.00	1.15	1.15	1.30	1.15	5.00	5.10	5.25	5.05	5.60	$J^{(1)}_{n,T}$	10	1.15	1.30	1.30	1.45	1.35	5.30	5.45	5.80	6.05	7.55
		20	0.95	0.85	1.25	1.20	1.15	5.10	5.20	5.30	4.40	5.70		20	0.95	0.95	1.30	1.40	1.50	5.30	5.50	5.60	5.80	7.80
		30	0.95	1.05	1.05	0.95	1.00	5.10	5.05	5.45	4.75	5.00		30	0.95	1.00	1.25	1.10	1.80	5.15	5.60	5.50	6.15	7.25
		50	0.90	1.00	1.00	0.95	1.00	4.90	4.75	5.05	5.20	5.20		50	1.15	1.15	1.10	1.00	1.70	5.30	5.50	5.65	6.10	7.35
		100	0.95	1.00	0.95	1.00	1.30	5.05	4.80	5.15	5.00	5.15		100	1.00	1.05	1.55	1.10	2.00	5.40	5.35	6.15	6.10	8.00
		200	0.95	0.95	0.90	1.00	0.75	4.85	5.00	4.95	5.00	5.05		200	1.15	1.10	1.15	1.15	1.55	5.35	5.45	5.70	5.90	8.40
Truncated	$S^{(2)}_{n,T}$	10	1.00	1.05	1.00	1.20	1.05	4.90	5.05	5.20	5.10	5.25	$J^{(2)}_{n,T}$	10	1.60	2.65	2.55	5.75	15.10	6.30	8.80	11.65	17.50	32.75
		20	0.90	0.90	1.25	1.20	1.00	4.95	5.10	4.85	4.50	5.65		20	0.50	0.75	1.10	0.80	2.55	3.65	3.50	5.00	6.15	7.55
		30	0.95	0.95	1.05	0.90	1.10	5.05	4.95	5.30	5.00	5.05		30	0.70	0.75	1.40	0.85	1.95	3.45	4.85	4.70	5.40	8.05
		50	0.90	1.05	1.00	0.95	1.00	5.05	4.85	5.15	5.20	5.10		50	0.80	0.75	0.95	1.30	2.30	3.95	4.80	5.50	6.45	10.80
		100	1.10	1.10	1.05	0.95	1.30	5.05	4.95	5.30	4.95	5.25		100	0.65	1.10	1.35	2.10	2.45	4.25	6.30	7.55	8.45	18.10
		200	1.05	1.05	1.15	1.05	0.95	5.05	5.00	5.15	5.00	5.20		200	0.45	0.75	0.60	0.90	1.55	3.40	3.55	3.90	6.05	8.25
Bartlett	$S^{(2)}_{n,T}$	10	1.00	1.15	1.15	1.30	1.15	5.00	5.10	5.25	5.05	5.60	$J^{(2)}_{n,T}$	10	1.15	1.30	1.30	1.45	1.35	5.30	5.45	5.80	6.05	7.55
		20	1.00	0.90	1.30	1.20	1.05	4.95	5.25	4.85	4.60	5.80		20	1.05	1.25	1.65	2.70	8.65	5.90	7.10	9.15	15.25	41.45
		30	0.85	0.90	1.05	0.90	1.05	5.10	5.20	5.35	5.00	4.90		30	1.05	1.55	2.30	3.55	11.90	5.60	8.50	10.10	16.70	52.85
		50	0.95	0.95	1.00	0.95	1.00	5.00	4.75	5.05	5.20	5.05		50	1.30	1.45	2.20	4.10	18.85	6.10	8.60	10.75	22.00	69.60
		100	1.05	1.05	1.10	1.00	1.35	5.35	5.00	5.25	5.10	5.30		100	1.00	2.30	4.65	9.45	90.10	7.85	14.65	27.80	62.35	99.85
		200	1.05	0.95	1.10	1.05	0.90	4.95	4.90	5.20	5.00	5.15		200	0.70	1.95	4.60	16.40	98.65	5.75	12.35	30.65	81.80	99.65
Parzen	$S^{(2)}_{n,T}$	10	1.00	1.15	1.15	1.30	1.15	5.00	5.10	5.25	5.05	5.60	$J^{(2)}_{n,T}$	10	1.15	1.30	1.30	1.45	1.35	5.30	5.45	5.80	6.05	7.55
		20	0.85	0.95	1.30	1.25	1.05	5.10	5.20	5.15	4.55	5.65		20	1.05	0.95	1.25	1.55	2.10	5.40	5.80	5.90	7.25	10.90
		30	0.85	1.00	1.10	0.95	1.00	5.10	5.25	5.45	4.85	4.80		30	0.95	1.20	1.30	1.60	2.20	5.50	6.40	6.25	7.10	10.45
		50	0.95	1.05	1.05	0.95	1.05	4.90	4.85	4.95	5.15	5.00		50	1.10	1.25	1.35	1.55	3.20	5.30	6.10	6.35	8.25	12.70
		100	1.05	1.00	1.10	1.00	1.40	5.40	5.00	5.30	5.10	5.30		100	1.25	1.95	3.45	3.80	40.65	6.90	10.00	14.95	27.45	91.95
		200	1.10	1.00	1.10	1.05	0.85	4.95	4.95	5.10	5.05	5.15		200	1.25	2.10	2.80	5.85	43.20	7.25	9.70	17.10	35.80	99.50
Tukey	$S^{(2)}_{n,T}$	10	1.00	1.15	1.15	1.30	1.15	5.00	5.10	5.25	5.05	5.60	$J^{(2)}_{n,T}$	10	1.15	1.30	1.30	1.45	1.35	5.30	5.45	5.80	6.05	7.55
		20	0.95	0.90	1.30	1.20	1.05	5.10	5.25	4.85	4.60	5.75		20	1.10	1.10	2.30	3.10	5.10	5.65	7.30	10.35	16.10	24.40
		30	0.85	0.90	1.05	0.90	1.05	5.10	5.25	5.35	5.00	4.90		30	1.10	1.50	2.35	2.25	7.40	5.65	8.25	10.70	17.90	35.40
		50	0.95	1.00	1.00	0.95	1.00	4.95	4.80	5.10	5.20	5.05		50	0.90	2.15	2.15	1.95	6.00	6.15	8.25	11.95	12.35	39.95
		100	1.05	1.05	1.10	1.00	1.40	5.35	5.00	5.30	5.15	5.30		100	1.30	2.00	1.75	4.60	10.05	6.65	15.65	22.55	35.70	62.85
		200	1.10	1.00	1.05	1.05	0.90	4.95	4.90	5.15	5.05	5.10		200	1.20	2.20	2.00	4.35	10.05	5.90	8.40	12.90	35.45	58.25
QS	$S^{(2)}_{n,T}$	10	1.00	1.10	1.10	1.35	1.10	5.00	5.05	5.35	5.00	5.45	$J^{(2)}_{n,T}$	10	1.20	1.15	1.20	1.55	1.45	5.30	5.70	5.80	6.25	8.85
		20	1.00	0.90	1.30	1.20	1.00	5.00	5.15	4.85	4.60	5.75		20	1.40	2.00	5.85	30.35	73.00	8.20	18.15	31.35	66.95	93.65
		30	0.80	0.90	1.05	0.90	1.05	5.15	5.05	5.35	5.00	4.85		30	1.70	3.60	7.20	34.05	84.05	7.85	20.50	33.45	72.80	97.45
		50	0.95	0.95	1.00	0.95	0.95	4.95	4.85	5.10	5.20	5.00		50	1.65	2.75	12.05	42.65	97.15	9.15	21.30	44.80	85.05	99.75
		100	1.05	1.05	1.05	0.95	1.35	5.35	5.00	5.25	5.00	5.30		100	2.75	38.10	76.50	99.60	100.00	23.90	83.15	99.55	100.00	100.00
		200	1.05	0.95	1.15	1.05	0.90	5.00	4.90	5.20	5.00	5.20		200	3.35	36.80	93.55	100.00	100.00	18.20	91.75	100.00	100.00	100.00
	$S^{(3)}_{n,T}$	10	1.15	1.05	1.15	1.35	1.00	5.30	5.25	5.50	5.00	5.50	$J^{(3)}_{n,T}$	10		38.90	80.20	95.20	99.85		70.25	90.70	97.95	100.00
		20	0.95	0.95	1.00	1.15	1.00	5.20	5.20	4.95	4.35	5.60		20			58.00	99.10	100.00			84.20	99.65	100.00
		30	0.95	0.85	1.05	0.90	1.10	5.15	5.15	5.50	4.90	4.75		30				97.80	100.00				99.50	100.00
		50	0.95	1.10	0.90	1.05	0.95	5.15	4.95	5.15	5.10	5.35		50					100.00					100.00
		100	1.05	1.05	1.05	1.00	1.40	5.10	5.05	5.20	5.10	5.05		100										
		200	1.15	0.95	0.95	1.00	1.20	5.10	5.10	5.15	4.90	5.25		200										
Fixed	$S^{(4)}_{n,T}$	10	1.20	1.05	1.10	1.30	1.00	5.30	5.25	5.55	5.05	5.50	$J^{(4)}_{n,T}$	10	2.05	7.35	17.90	61.95	89.00	10.80	29.75	53.05	81.55	96.40
		20	0.95	0.90	1.00	1.15	1.00	5.20	5.25	4.95	4.35	5.55		20	1.55	5.80	11.25	32.20	90.20	8.50	18.80	38.95	72.70	98.95
		30	0.95	0.85	1.10	0.90	1.10	5.15	5.20	5.45	4.90	4.80		30	1.90	3.20	6.85	24.35	82.40	8.60	16.40	31.15	64.80	98.60
		50	0.95	1.10	0.90	1.00	0.95	5.05	4.95	5.20	5.25	5.35		50	1.90	3.55	3.60	18.65	79.05	7.00	13.95	26.70	56.65	98.25
		100	1.05	1.05	1.05	1.00	1.40	5.10	5.05	5.20	5.10	5.05		100	1.50	2.95	6.30	15.20	76.60	7.85	12.55	21.55	45.75	98.40
		200	1.15	0.95	0.95	1.00	1.20	5.10	5.10	5.10	4.90	5.25		200	1.35	5.35	4.25	23.80	96.00	7.85	17.85	25.90	65.25	99.90
Expanding	$S^{(4)}_{n,T}$	10	1.10	1.05	1.10	1.35	1.00	5.15	5.15	5.45	5.05	5.50	$J^{(4)}_{n,T}$	10	2.35	3.95	6.50	14.25	57.55	8.15	14.40	25.55	50.65	86.85
		20	0.95	0.90	1.00	1.15	1.00	5.20	5.25	4.95	4.35	5.55		20	1.55	5.80	11.25	32.20	90.20	8.50	18.80	38.95	72.70	98.95
		30	0.95	0.85	1.10	0.90	1.10	5.15	5.20	5.45	4.90	4.80		30	1.90	3.20	6.85	24.35	82.40	8.60	16.40	31.15	64.80	98.60
		50	0.95	1.10	0.90	1.00	0.95	5.05	4.95	5.20	5.25	5.35		50	1.90	3.55	3.60	18.65	79.05	7.00	13.95	26.70	56.65	98.25
		100	1.05	1.05	1.05	1.00	1.40	5.10	5.05	5.20	5.10	5.05		100	1.40	3.00	5.95	21.90	91.90	6.40	13.30	24.70	57.90	99.55
		200	1.15	0.95	0.95	1.00	1.20	5.10	5.10	5.15	4.90	5.25		200	1.65	4.95	8.30	37.05	99.40	7.60	16.00	29.00	76.00	100.00
Fixed	$S^{(5)}_{n,T}$	10	1.10	1.05	1.10	1.30	1.00	5.15	5.20	5.50	5.05	5.50	$J^{(5)}_{n,T}$	10	0.85	1.80	2.30	6.30	11.05	6.00	11.85	22.30	50.55	72.75
		20	0.95	0.95	1.00	1.15	0.95	5.30	5.25	5.00	4.35	5.65		20	0.30	1.00	1.05	1.55	5.65	2.90	5.50	9.10	25.90	51.75
		30	0.90	0.85	1.10	0.90	1.10	5.15	5.25	5.50	4.90	4.65		30	0.55	0.90	1.05	2.70	4.20	3.55	6.60	7.45	14.10	37.75
		50	0.95	1.10	0.90	1.00	0.95	5.25	5.00	5.20	5.20	5.20		50	1.00	0.65	1.20	1.80	3.80	3.45	6.55	7.50	13.60	30.60
		100	1.00	1.05	1.10	1.00	1.40	5.15	4.95	5.15	5.05	5.05		100	0.50	0.60	1.65	1.40	4.85	3.40	5.25	7.20	15.10	26.75
		200	1.15	0.95	0.90	1.00	1.05	5.05	5.05	5.15	4.95	5.25		200	0.50	1.25	0.95	2.00	2.75	3.15	4.45	5.00	9.00	19.10
Expanding	$S^{(5)}_{n,T}$	10	1.10	1.05	1.10	1.30	1.05	5.05	5.15	5.45	5.05	5.30	$J^{(5)}_{n,T}$	10	0.80	1.55	1.70	4.10	9.20	5.80	9.90	12.05	32.40	50.55
		20	0.95	0.95	1.00	1.15	0.95	5.30	5.25	5.00	4.35	5.65		20	0.30	1.00	1.05	1.55	5.65	2.90	5.50	9.10	25.90	51.75
		30	0.90	0.85	1.10	0.90	1.10	5.15	5.25	5.50	4.90	4.65		30	0.55	0.90	1.05	2.70	4.20	3.55	6.60	7.45	14.10	37.75
		50	0.95	1.10	0.90	1.00	0.95	5.25	5.00	5.20	5.20	5.20		50	1.00	0.65	1.20	1.80	3.80	3.45	6.55	7.50	13.60	30.60
		100	1.05	1.05	1.10	1.00	1.40	5.25	4.95	5.15	5.10	5.05		100	0.30	0.45	1.10	1.30	2.85	3.25	4.80	5.65	10.40	20.85
		200	1.15	0.95	0.90	1.00	1.10	5.10	5.05	5.10	4.95	5.25		200	0.65	0.85	1.05	1.05	2.35	2.80	3.25	5.45	8.20	18.85

Appendix C

Additional Results for Chapter 3

Table C1: Mean Relative RMSE for Direct Prediction Method - Consumer Price Inflation

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.00	1.02	1.05	1.05	1.02	1.03	1.02	1.07	1.02	1.03	1.04	1.06	1.04	1.04	1.08	1.13	1.00	**0.99**	1.03	1.07
			4	1.01	1.02	1.03	1.07	1.01	1.02	1.04	1.07	1.01	1.02	1.04	1.07	1.00	**0.98**	1.04	1.08	1.00	1.00	1.06	1.10
			8	1.00	1.00	1.04	1.07	1.00	1.00	1.05	1.08	1.00	1.00	1.05	1.08	1.00	**0.98**	1.02	1.06	1.00	1.00	1.04	1.07
ARDL	$\mathbf{x}_{1,it}$		2	1.00	1.00	1.03	**0.99**	1.01	1.00	1.00	**0.99**	1.01	1.00	1.02	**0.99**	1.08	1.05	1.07	1.08	1.02	1.00	1.03	1.02
			4	1.00	0.98	1.00	0.99	1.00	**0.98**	1.01	0.99	1.00	**0.98**	1.01	0.99	1.07	1.00	1.03	1.02	1.04	1.00	1.04	1.02
			8	1.03	0.99	1.01	0.97	1.03	0.99	1.01	0.97	1.03	0.99	1.01	0.97	1.08	1.00	0.98	**0.97**	1.03	0.99	1.00	0.97
ARDL	$\mathbf{x}_{2,it}$		2	1.00	1.01	**0.99**	1.02	1.01	1.01	0.99	1.02	1.01	1.01	0.99	1.02	1.06	1.02	1.03	1.07	1.01	0.99	1.01	1.02
			4	1.02	0.99	0.99	1.01	1.02	0.99	1.02	1.01	1.02	0.99	1.00	1.01	1.06	**0.99**	1.01	1.03	1.04	1.00	1.03	1.02
			8	1.05	**0.99**	1.02	1.00	1.05	**0.99**	1.02	1.00	1.05	**0.99**	1.02	1.00	1.12	1.05	1.02	1.02	1.05	1.01	1.02	1.00
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.13	1.07	1.10	1.07	1.13	1.14	1.10	**1.07**	1.13	1.10	1.10	1.07	1.13	1.10	1.14	1.15	1.11	1.12	1.14	1.15
			4	1.13	1.14	1.10	1.10	1.13	1.14	1.11	1.12	1.13	1.14	1.10	1.11	**1.10**	1.10	1.12	1.13	1.12	1.13	1.15	1.15
			8	1.07	1.07	1.08	1.06	1.07	1.07	1.10	1.09	1.07	1.07	1.09	1.08	1.06	**1.06**	1.07	1.07	1.06	1.06	1.09	1.09
FAR		*AVA*	2	1.02	1.00	0.96	0.97	1.02	1.03	0.96	0.97	1.02	1.03	0.96	0.97	0.99	0.98	0.98	0.99	**0.93**	0.94	0.93	0.94
			4	0.97	0.98	0.92	0.93	0.97	0.98	0.94	0.95	0.97	0.98	0.93	0.94	0.91	0.91	0.91	0.92	**0.88**	0.91	0.88	0.89
			8	0.98	0.99	0.98	0.98	0.98	0.99	1.00	0.99	0.98	0.99	0.99	0.99	0.98	1.02	0.99	0.99	**0.94**	0.97	0.96	0.96
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.17	1.18	1.10	**1.09**	1.17	1.18	1.11	1.11	1.17	1.18	1.10	1.10	1.12	1.16	1.19	1.16	1.14	1.16	1.18	1.17
			4	1.10	1.10	1.11	1.09	1.10	1.08	1.11	1.09	1.10	1.07	1.11	1.08	1.05	1.17	1.14	1.10	1.08	**1.03**	1.15	1.15
			8	**1.03**	1.09	1.05	1.04	**1.03**	1.07	1.06	1.05	**1.03**	1.06	1.05	1.05	1.06	1.20	1.08	1.06	1.03	1.07	1.07	1.05
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.02	2.18	0.96	0.95	1.02	2.29	0.96	0.96	1.02	2.26	0.96	0.95	1.03	2.88	1.04	1.01	0.93	2.51	0.94	**0.92**
			4	0.99	2.52	0.93	0.91	0.99	2.69	0.93	0.91	0.99	2.69	0.93	0.91	1.00	4.30	0.96	0.95	0.91	3.41	0.89	**0.88**
			8	1.02	2.22	0.97	0.96	1.02	2.02	0.98	0.98	1.02	2.10	0.97	0.97	1.04	3.26	0.98	0.99	0.97	2.65	0.95	**0.95**
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.18	1.21	1.11	**1.09**	1.18	1.21	1.12	1.10	1.18	1.21	1.12	1.09	1.25	1.16	1.13	1.10	1.15	1.20	1.19	1.13
			4	1.11	1.01	1.05	1.05	1.11	**0.97**	1.06	1.05	1.11	**0.97**	1.05	1.05	1.22	1.23	1.16	1.06	1.10	1.10	1.09	1.11
			8	**1.02**	1.04	1.06	1.03	**1.02**	1.02	1.06	1.06	**1.02**	1.02	1.05	1.05	1.15	1.33	1.07	1.04	1.04	1.05	1.06	1.05
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.06	2.17	0.98	0.95	1.06	2.32	0.98	0.95	1.06	2.21	0.98	0.95	1.30	3.25	1.05	0.99	0.99	2.38	0.94	**0.92**
			4	0.99	2.78	0.92	0.90	0.99	3.07	0.92	0.90	0.99	3.00	0.92	0.90	1.17	3.70	0.94	0.92	0.93	2.85	0.91	**0.88**
			8	1.01	2.28	0.96	0.96	1.01	2.33	0.97	0.97	1.01	2.28	0.96	0.96	1.19	3.06	0.99	1.01	1.05	2.53	0.96	**0.95**

Notes: The results show the mean relative RMSE of each model and estimator made by direct method, relative to the RMSE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. "Long Lag" stands for $p = 4$, $q = 4$, whereas "Short Lag" stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \mathrm{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\mathrm{UNR}_{it}, \Delta \log \mathrm{XMKT}_{it})'$.

Table C2: Mean Relative RMSE for Iterated Prediction Method - Consumer Price Inflation

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.04	1.05	1.05	1.10	1.04	1.05	1.05	1.07	1.04	1.05	1.05	1.10	1.05	1.05	1.10	1.17	1.02	**1.02**	1.07	1.12
			4	0.98	0.99	1.02	1.05	0.98	0.99	1.02	1.03	0.98	0.99	1.02	1.05	1.01	1.02	1.08	1.16	**0.95**	0.96	1.01	1.06
			8	1.00	1.01	1.01	1.05	1.00	1.01	1.01	1.05	1.00	1.01	1.01	1.05	1.00	1.00	1.02	1.05	**0.99**	1.00	1.02	1.05
ARDL	$\mathbf{x}_{1,it}$		2	1.01	1.02	1.03	**1.01**	1.01	1.02	1.03	1.01	1.01	1.02	1.03	1.01	1.08	1.06	1.08	1.10	1.03	1.02	1.06	1.05
			4	**0.94**	0.94	0.99	0.96	**0.94**	0.94	0.99	0.96	**0.94**	0.94	0.99	0.96	1.01	1.00	1.05	1.06	0.95	0.94	0.99	0.98
			8	0.99	0.98	**0.97**	1.01	0.99	0.98	**0.97**	1.01	0.99	0.98	**0.97**	1.01	1.02	1.01	0.99	1.02	1.00	0.99	0.99	1.02
ARDL	$\mathbf{x}_{2,it}$		2	1.01	1.01	**0.96**	1.06	1.01	1.01	**0.96**	1.04	1.01	1.01	**0.96**	1.05	1.02	1.00	1.02	1.07	1.00	0.99	1.03	1.07
			4	0.95	0.95	**0.92**	1.04	0.95	0.95	**0.92**	1.01	0.95	0.95	**0.92**	1.03	0.96	0.94	0.98	1.04	0.93	0.92	0.96	1.02
			8	1.00	0.99	**0.95**	1.12	1.00	0.99	**0.95**	1.08	1.00	0.99	**0.95**	1.11	1.00	0.99	0.97	1.06	0.98	0.97	0.97	1.07
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.18	1.12	**1.10**	1.11	1.18	1.18	1.10	1.11	1.18	1.18	1.10	1.11	1.12	1.12	1.16	1.17	1.13	1.11	1.18	1.17
			4	1.15	1.08	1.09	1.09	1.15	1.16	1.08	1.09	1.15	1.16	1.08	1.09	**1.07**	1.08	1.14	1.15	1.09	1.09	1.16	1.15
			8	1.05	**1.02**	1.02	1.03	1.05	1.05	1.02	1.03	1.05	1.05	1.02	1.03	1.04	**1.02**	1.03	1.04	1.02	1.04	1.04	1.04
FAR		*AVA*	2	1.08	0.96	0.96	0.97	1.08	1.04	0.96	0.97	1.08	1.04	0.96	0.97	0.98	0.95	0.98	0.99	0.94	**0.92**	0.97	0.96
			4	1.00	0.90	0.92	0.93	1.00	0.96	0.92	0.94	1.00	0.96	0.92	0.94	0.89	0.85	0.90	0.91	0.87	**0.84**	0.91	0.90
			8	1.01	0.95	0.98	0.99	1.01	0.97	0.98	0.99	1.01	0.97	0.98	0.99	1.07	1.03	1.06	1.06	0.98	**0.92**	0.98	0.98
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.20	**1.12**	1.14	1.14	1.19	1.16	1.14	1.14	1.19	1.13	1.14	1.14	1.16	1.14	1.18	1.17	1.18	1.22	1.16	1.13
			4	1.14	1.14	1.09	**1.08**	1.14	1.17	1.09	**1.08**	1.14	1.13	1.09	**1.08**	1.12	1.14	1.15	1.13	1.12	1.19	1.13	1.10
			8	1.04	1.06	0.99	**0.99**	1.06	1.04	0.99	**0.99**	1.06	1.03	0.99	**0.99**	1.04	1.12	1.01	1.01	1.02	1.11	1.00	1.01
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.06	2.77	0.96	0.96	1.06	3.26	0.96	0.95	1.06	3.01	0.96	0.95	1.05	2.95	1.03	1.00	**0.95**	2.74	0.97	0.95
			4	0.96	2.88	0.91	0.91	0.97	3.78	0.91	0.91	0.97	3.14	0.91	0.91	0.97	3.71	0.96	0.93	**0.88**	3.06	0.90	0.89
			8	1.01	4.46	**0.96**	0.97	1.02	>5	**0.96**	0.96	1.02	>5	**0.96**	0.96	1.11	>5	1.04	1.06	1.00	>5	1.00	1.00
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.14	1.14	1.14	1.11	1.14	1.13	1.12	1.11	1.14	1.13	1.12	1.11	1.30	1.29	1.13	**1.09**	1.17	1.10	1.14	1.11
			4	1.12	1.16	1.10	1.05	1.12	1.17	1.10	1.05	1.12	1.16	1.10	1.05	1.28	1.35	1.07	**1.03**	1.12	1.06	1.10	1.06
			8	1.00	1.09	1.01	0.99	1.00	1.08	1.00	0.99	1.00	1.07	1.00	0.99	1.12	1.50	**0.96**	0.99	1.04	1.07	0.99	1.00
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.07	2.58	0.98	0.95	1.07	2.83	0.98	**0.95**	1.07	2.61	0.98	**0.95**	1.37	3.61	1.06	0.97	1.02	3.06	0.98	0.96
			4	0.97	3.28	0.93	0.91	0.97	3.70	0.93	0.91	0.97	3.37	0.93	0.91	1.36	>5	0.93	0.91	0.92	2.95	0.90	**0.90**
			8	1.01	>5	0.97	**0.96**	1.01	>5	0.97	**0.96**	1.01	>5	0.97	**0.96**	1.27	>5	1.04	1.05	1.03	>5	1.00	1.00

Notes: The results show the mean relative RMSE of each model and estimator made by iterated method, relative to the RMSE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. "Long Lag" stands for $p = 4$, $q = 4$, whereas "Short Lag" stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \text{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\text{UNR}_{it}, \Delta \log \text{XMKT}_{it})'$.

Table C3: Mean Relative MAE for Direct Prediction Method - Consumer Price Inflation

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.00	1.02	1.06	1.06	1.02	1.03	1.02	1.09	1.02	1.03	1.04	1.07	1.04	1.04	1.10	1.15	1.00	**1.00**	1.05	1.09
			4	1.02	1.03	1.05	1.10	1.02	1.03	1.06	1.10	1.02	1.03	1.06	1.10	1.00	**0.98**	1.06	1.11	1.00	1.00	1.10	1.14
			8	1.01	1.02	1.06	1.09	1.01	1.02	1.07	1.10	1.01	1.02	1.07	1.10	1.00	**0.98**	1.04	1.08	1.00	1.00	1.06	1.09
ARDL	$\mathbf{x}_{1,it}$		2	1.01	1.01	1.04	1.00	1.02	1.01	**1.00**	1.00	1.02	1.01	1.02	1.00	1.11	1.06	1.09	1.10	1.04	1.02	1.04	1.03
			4	1.01	0.99	1.00	1.00	1.01	**0.98**	1.01	1.00	1.01	**0.98**	1.01	1.00	1.08	1.01	1.03	1.03	1.06	1.01	1.06	1.04
			8	1.06	0.99	1.02	0.97	1.06	0.99	1.03	0.97	1.06	0.99	1.03	**0.97**	1.09	1.01	0.99	0.97	1.03	0.98	1.02	0.97
ARDL	$\mathbf{x}_{2,it}$		2	1.00	1.00	1.00	1.03	1.01	1.00	1.00	1.03	1.01	1.00	1.00	1.03	1.07	1.02	1.04	1.09	1.02	**0.99**	1.02	1.04
			4	1.02	1.00	0.98	1.03	1.02	1.00	1.02	1.03	1.02	1.00	0.99	1.03	1.05	**0.97**	1.00	1.04	1.04	0.99	1.05	1.04
			8	1.07	1.00	1.03	**0.99**	1.07	1.00	1.04	0.99	1.07	1.00	1.04	1.00	1.13	1.04	1.04	1.02	1.04	1.00	1.04	0.99
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.13	**1.08**	1.12	1.09	1.13	1.13	1.12	1.08	1.13	1.10	1.12	1.09	1.13	1.11	1.15	1.16	1.12	1.12	1.15	1.16
			4	1.13	1.14	1.11	1.11	1.13	1.14	1.11	1.12	1.13	1.14	1.11	1.11	**1.08**	1.09	1.13	1.15	1.11	1.13	1.18	1.18
			8	1.10	1.10	1.11	1.09	1.10	1.10	1.13	1.12	1.10	1.10	1.12	1.11	**1.07**	1.08	1.10	1.10	1.08	1.08	1.12	1.12
FAR		*AVA*	2	1.02	1.01	0.97	0.99	1.02	1.03	0.98	0.98	1.02	1.03	0.97	0.99	0.99	0.99	1.00	1.01	**0.93**	0.94	0.93	0.94
			4	0.98	1.00	0.94	0.95	0.98	1.00	0.96	0.96	0.98	1.00	0.95	0.95	0.91	0.92	0.91	0.92	**0.87**	0.91	0.89	0.89
			8	1.00	0.99	0.99	0.99	1.00	0.99	1.02	1.01	1.00	0.99	1.01	1.00	0.97	1.01	0.97	0.97	**0.93**	0.96	0.95	0.95
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.16	1.18	1.11	**1.10**	1.16	1.18	1.12	1.11	1.16	1.18	1.11	1.10	1.13	1.18	1.20	1.17	1.14	1.19	1.18	1.17
			4	1.11	1.08	1.12	1.08	1.11	1.07	1.11	1.09	1.11	1.05	1.11	1.08	**1.04**	1.20	1.14	1.10	1.08	1.07	1.17	1.16
			8	1.05	1.09	1.08	1.07	1.05	1.06	1.09	1.08	1.05	1.05	1.08	1.07	1.08	1.21	1.12	1.09	**1.04**	1.08	1.10	1.09
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.02	2.36	0.97	0.96	1.02	2.52	0.97	0.97	1.02	2.46	0.97	0.96	1.04	3.05	1.06	1.03	0.92	2.67	0.94	**0.92**
			4	0.99	2.59	0.93	0.91	0.99	2.83	0.93	0.91	0.99	2.83	0.93	0.91	1.00	4.97	0.95	0.94	0.89	3.74	0.89	**0.87**
			8	1.03	2.30	0.97	0.97	1.03	2.09	0.99	0.98	1.03	2.19	0.98	0.97	1.04	3.30	0.95	0.96	0.97	2.80	0.94	**0.93**
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.17	1.21	1.13	1.10	1.17	1.20	1.14	1.12	1.17	1.20	1.13	1.10	1.26	1.18	1.14	**1.10**	1.15	1.22	1.19	1.13
			4	1.12	1.01	1.04	1.04	1.12	**1.00**	1.05	1.05	1.12	**1.00**	1.04	1.04	1.24	1.27	1.17	1.06	1.11	1.12	1.10	1.12
			8	1.03	1.04	1.09	1.05	1.03	**1.02**	1.09	1.08	1.03	**1.02**	1.08	1.07	1.18	1.31	1.11	1.07	1.03	1.06	1.10	1.08
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.06	2.36	0.99	0.96	1.06	2.51	0.99	0.97	1.06	2.41	0.99	0.96	1.30	3.60	1.08	1.01	0.98	2.73	0.94	**0.92**
			4	1.00	3.16	0.92	0.90	1.00	3.57	0.92	0.90	1.00	3.46	0.92	0.90	1.19	3.90	0.94	0.92	0.91	3.13	0.90	**0.87**
			8	1.01	2.45	0.96	0.95	1.01	2.43	0.98	0.97	1.01	2.41	0.96	0.96	1.22	3.20	0.96	0.97	1.06	2.68	0.94	**0.94**

Notes: The results show the mean relative MAE of each model and estimator made by direct method, relative to the MAE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. “Long Lag” stands for $p = 4$, $q = 4$, whereas “Short Lag” stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \mathrm{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\mathrm{UNR}_{it}, \Delta \log \mathrm{XMKT}_{it})'$.

Table C4: Mean Relative MAE for Iterated Prediction Method - Consumer Price Inflation

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.04	1.05	1.05	1.11	1.04	1.05	1.05	1.08	1.04	1.05	1.05	1.11	1.06	1.05	1.11	1.20	**1.02**	1.02	1.08	1.14
			4	1.00	1.01	1.04	1.08	1.00	1.01	1.04	1.06	1.00	1.01	1.04	1.08	1.02	1.03	1.13	1.21	**0.96**	0.97	1.05	1.11
			8	1.01	1.02	1.03	1.07	1.01	1.02	1.03	1.07	1.01	1.02	1.03	1.07	1.01	1.01	1.04	1.08	**1.00**	1.01	1.03	1.07
ARDL	$\mathbf{x}_{1,it}$		2	1.02	**1.02**	1.04	1.02	1.02	**1.02**	1.04	1.03	1.02	**1.02**	1.04	1.03	1.10	1.06	1.10	1.12	1.05	1.03	1.07	1.07
			4	0.95	**0.94**	0.99	0.99	0.95	**0.94**	0.99	0.99	0.95	**0.94**	0.99	0.99	1.03	1.01	1.07	1.09	0.96	0.95	1.01	1.01
			8	1.00	0.99	**0.98**	1.01	1.00	0.99	**0.98**	1.02	1.00	0.99	**0.98**	1.02	1.04	1.02	1.00	1.03	1.00	0.99	1.00	1.02
ARDL	$\mathbf{x}_{2,it}$		2	1.02	1.01	**0.97**	1.07	1.02	1.01	**0.97**	1.05	1.02	1.01	**0.97**	1.07	1.03	0.99	1.03	1.09	1.00	0.98	1.04	1.09
			4	0.96	0.95	**0.91**	1.10	0.96	0.95	**0.91**	1.05	0.96	0.95	**0.91**	1.08	0.97	0.94	0.99	1.10	0.93	0.92	0.98	1.07
			8	1.01	0.99	**0.95**	1.15	1.01	0.99	**0.95**	1.10	1.01	0.99	**0.95**	1.13	1.01	1.00	0.98	1.07	0.98	0.97	0.98	1.09
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.18	1.12	1.12	1.12	1.18	1.18	1.12	1.12	1.18	1.18	1.12	1.12	1.12	1.12	1.17	1.18	1.13	**1.10**	1.18	1.18
			4	1.17	1.08	1.10	1.11	1.17	1.18	1.09	1.10	1.17	1.18	1.09	1.10	**1.07**	1.08	1.16	1.17	1.09	1.10	1.18	1.17
			8	1.05	**1.01**	1.03	1.04	1.05	1.05	1.03	1.03	1.05	1.05	1.03	1.03	1.02	**1.01**	1.04	1.04	1.01	1.03	1.04	1.04
FAR		*AVA*	2	1.09	0.97	0.97	0.98	1.09	1.04	0.97	0.98	1.09	1.04	0.97	0.98	0.99	0.95	1.00	1.00	0.94	**0.91**	0.97	0.97
			4	1.02	0.91	0.95	0.95	1.02	0.99	0.95	0.96	1.02	0.99	0.95	0.96	0.89	0.85	0.90	0.91	0.86	**0.83**	0.91	0.91
			8	1.02	0.95	0.99	1.00	1.02	0.98	0.99	1.00	1.02	0.98	0.99	1.00	1.06	1.03	1.04	1.04	0.97	**0.91**	0.98	0.98
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.20	1.14	1.15	1.14	1.18	1.16	1.15	1.14	1.18	1.14	1.15	1.14	1.16	1.16	1.18	1.16	1.17	1.23	1.16	**1.13**
			4	1.17	1.14	1.11	**1.09**	1.17	1.19	1.11	**1.09**	1.17	1.15	1.11	**1.09**	1.13	1.14	1.18	1.16	1.13	1.22	1.15	1.11
			8	1.05	1.03	1.00	**1.00**	1.07	1.05	1.00	**1.00**	1.07	1.03	1.00	**1.00**	1.05	1.14	1.04	1.03	1.04	1.13	1.01	1.02
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.09	2.88	0.97	0.97	1.08	3.56	0.97	0.96	1.08	3.14	0.97	0.96	1.07	3.17	1.05	1.01	**0.94**	2.85	0.98	0.95
			4	0.98	3.13	0.92	0.91	0.98	3.38	0.92	0.91	0.98	3.30	0.92	0.91	0.96	3.95	0.95	0.92	**0.88**	3.49	0.90	0.89
			8	1.01	4.92	0.97	0.97	1.02	>5	0.97	**0.97**	1.02	>5	0.97	0.97	1.10	>5	1.01	1.03	0.99	>5	0.99	0.99
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.15	1.16	1.13	1.11	1.15	1.15	1.12	1.11	1.15	1.15	1.12	1.11	1.31	1.34	1.14	**1.09**	1.15	1.11	1.14	1.11
			4	1.13	1.17	1.12	1.06	1.13	1.18	1.10	1.06	1.13	1.17	1.10	1.06	1.28	1.30	1.09	**1.04**	1.12	1.06	1.11	1.07
			8	1.00	1.10	1.02	1.00	1.00	1.09	1.02	1.00	1.00	1.09	1.02	1.00	1.12	1.41	**0.96**	0.98	1.06	1.09	0.99	1.00
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.09	2.79	0.99	0.96	1.09	2.97	0.99	**0.96**	1.09	2.82	0.99	**0.96**	1.40	3.82	1.09	0.98	1.01	3.43	0.98	0.96
			4	0.98	3.89	0.94	0.91	0.98	4.11	0.94	0.91	0.98	4.00	0.94	0.91	1.37	>5	0.92	0.90	0.91	3.45	**0.90**	0.90
			8	1.02	>5	0.98	**0.96**	1.02	>5	0.98	**0.96**	1.02	>5	0.98	**0.96**	1.28	>5	1.01	1.02	1.02	>5	0.99	1.00

Notes: The results show the mean relative MAE of each model and estimator made by iterated method, relative to the MAE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. “Long Lag” stands for $p = 4$, $q = 4$, whereas “Short Lag” stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \mathrm{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\mathrm{UNR}_{it}, \Delta \log \mathrm{XMKT}_{it})'$.

Table C5: Median Relative RMSE for Direct Prediction Method - Consumer Price Inflation

				AIC				BIC				HQ				Long Lag				Short Lag			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.00	1.01	1.02	1.00	1.02	1.03	**0.98**	1.02	1.02	1.03	1.01	1.01	1.04	1.04	1.04	1.08	1.00	1.00	0.99	1.02
			4	1.00	1.00	**0.96**	0.98	1.00	1.00	0.97	0.98	1.00	1.00	0.97	0.98	1.01	0.99	0.97	0.99	1.00	0.99	0.98	1.01
			8	1.00	1.00	1.00	1.03	1.00	1.00	1.01	1.04	1.00	1.00	1.00	1.04	1.01	**0.99**	1.00	1.02	1.00	1.00	1.00	1.05
ARDL	$\mathbf{x}_{1,it}$		2	1.01	1.01	1.02	**0.97**	1.01	1.01	0.98	**0.97**	1.01	1.01	1.00	**0.97**	1.08	1.03	1.04	1.06	1.00	0.99	1.00	1.01
			4	1.01	0.99	0.98	**0.98**	1.01	0.99	0.99	0.98	1.01	0.99	0.99	**0.98**	1.04	1.01	0.99	1.02	1.01	1.01	1.02	1.03
			8	0.99	**0.97**	0.99	0.99	0.99	**0.97**	0.99	0.99	0.99	**0.97**	0.99	0.99	1.05	1.00	0.97	0.97	1.01	1.00	0.99	0.99
ARDL	$\mathbf{x}_{2,it}$		2	1.00	1.00	0.97	0.99	1.01	1.00	**0.97**	0.99	1.01	1.00	0.98	0.99	1.06	1.03	1.00	1.03	1.01	0.98	0.99	1.00
			4	1.02	1.00	0.98	0.98	1.02	1.00	0.99	0.98	1.02	1.00	**0.97**	0.98	1.05	0.99	0.98	0.99	1.02	0.99	1.02	1.02
			8	1.01	**0.98**	1.01	0.99	1.01	**0.98**	1.01	1.01	1.01	**0.98**	1.01	1.01	1.11	1.02	1.01	1.00	1.04	1.00	1.01	0.99
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.13	1.07	1.11	1.06	1.13	1.12	1.10	**1.05**	1.13	1.09	1.10	1.06	1.13	1.10	1.12	1.12	1.12	1.13	1.11	1.12
			4	1.11	1.11	1.09	**1.08**	1.11	1.11	1.09	1.09	1.11	1.11	1.09	1.09	1.09	1.11	1.10	1.11	1.09	1.10	1.11	1.11
			8	1.07	1.07	1.04	**1.04**	1.07	1.07	1.07	1.06	1.07	1.07	1.07	1.07	1.05	1.06	1.05	1.05	1.05	1.06	1.08	1.07
FAR		*AVA*	2	1.03	1.00	0.97	0.97	1.02	1.03	0.97	0.97	1.02	1.02	0.96	0.96	0.96	0.98	0.97	0.98	**0.93**	0.96	0.95	0.95
			4	0.95	0.96	0.90	0.90	0.95	0.96	0.91	0.92	0.95	0.96	0.90	0.91	0.90	0.93	0.87	0.88	**0.87**	0.91	0.87	0.88
			8	0.99	0.98	0.98	0.97	0.99	0.98	0.99	0.99	0.99	0.98	0.99	0.98	0.93	0.96	0.88	**0.88**	0.96	1.02	0.97	0.97
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.18	1.17	1.09	**1.07**	1.18	1.19	1.10	1.08	1.18	1.19	1.09	1.08	1.09	1.10	1.17	1.15	1.13	1.14	1.16	1.16
			4	1.07	1.08	1.09	1.06	1.07	1.03	1.08	1.06	1.07	1.02	1.09	1.05	1.07	0.97	1.12	1.09	1.09	**0.96**	1.16	1.11
			8	1.02	1.02	1.03	1.03	1.02	1.03	1.03	1.03	1.02	1.03	1.03	1.03	**1.02**	1.09	1.06	1.04	1.05	1.04	1.04	1.03
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.02	1.50	0.95	0.93	1.02	1.35	0.95	0.95	1.02	1.43	0.94	0.93	1.03	2.45	1.00	0.98	0.94	1.78	**0.92**	0.92
			4	0.99	1.68	0.92	0.91	0.99	1.69	0.91	0.90	0.99	1.69	0.91	0.90	0.98	2.32	0.92	0.91	0.88	1.66	0.87	**0.86**
			8	1.04	2.01	0.96	0.96	1.04	1.65	0.97	0.96	1.04	1.83	0.95	0.97	1.03	2.68	**0.86**	0.87	1.01	2.11	0.93	0.93
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.15	1.13	1.10	1.09	1.15	1.13	1.10	1.09	1.15	1.13	1.11	1.09	1.15	**1.06**	1.08	1.07	1.15	1.12	1.17	1.12
			4	1.12	0.94	1.04	1.03	1.12	**0.90**	1.03	1.04	1.12	**0.90**	1.04	1.02	1.15	1.22	1.15	1.04	1.03	1.07	1.08	1.09
			8	0.98	1.01	1.05	1.01	0.98	1.00	1.04	1.03	0.98	1.00	1.03	1.03	0.99	1.13	1.04	1.03	1.03	**0.93**	1.04	1.02
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.02	1.64	0.96	0.93	1.02	1.86	0.96	0.95	1.02	1.60	0.96	0.93	1.19	2.21	1.01	0.97	0.97	1.36	0.92	**0.92**
			4	0.99	1.79	0.91	0.89	0.99	1.78	0.91	0.90	0.99	1.75	0.91	0.89	1.07	2.22	0.91	0.87	0.87	1.64	0.88	**0.86**
			8	1.03	1.81	0.95	0.97	1.03	1.68	0.96	0.96	1.03	1.77	0.96	0.96	1.07	2.74	**0.87**	0.89	1.08	1.91	0.95	0.96

Notes: The results show the median relative RMSE of each model and estimator made by direct method, relative to the RMSE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. “Long Lag” stands for $p = 4$, $q = 4$, whereas “Short Lag” stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \mathrm{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\mathrm{UNR}_{it}, \Delta \log \mathrm{XMKT}_{it})'$.

Table C6: Median Relative RMSE for Iterated Prediction Method - Consumer Price Inflation

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.03	1.04	1.02	1.05	1.04	1.04	1.02	1.01	1.04	1.04	1.02	1.05	1.06	1.04	1.06	1.11	1.01	**1.01**	1.01	1.06
			4	0.96	0.96	0.97	0.98	0.96	0.96	0.97	0.96	0.96	0.96	0.97	0.98	1.01	1.02	1.01	1.06	**0.94**	0.95	0.95	0.99
			8	0.99	0.99	0.99	1.02	0.99	0.99	0.99	1.02	0.99	0.99	0.99	1.02	**0.98**	0.99	0.99	1.02	0.99	0.99	0.99	1.02
ARDL	$\mathbf{x}_{1,it}$		2	1.03	1.01	1.00	**0.96**	1.03	1.01	1.00	0.97	1.03	1.01	1.00	0.97	1.07	1.04	1.05	1.05	1.02	1.02	1.02	1.01
			4	0.96	**0.94**	0.96	0.95	0.96	**0.94**	0.96	0.95	0.96	**0.94**	0.96	0.95	1.03	1.00	1.03	1.04	0.95	0.94	0.97	0.97
			8	0.98	**0.97**	0.98	0.99	0.98	**0.97**	0.98	0.99	0.98	**0.97**	0.98	0.99	1.03	1.01	0.98	1.00	1.01	1.00	0.98	0.99
ARDL	$\mathbf{x}_{2,it}$		2	1.03	1.01	**0.96**	1.00	1.03	1.01	**0.96**	0.98	1.03	1.01	**0.96**	1.01	1.00	0.99	1.01	1.01	1.01	0.99	0.99	1.01
			4	0.96	0.96	**0.91**	0.98	0.96	0.96	**0.91**	0.97	0.96	0.96	**0.91**	0.97	0.96	0.93	0.96	1.00	0.95	0.93	0.94	0.97
			8	0.98	0.96	**0.93**	0.99	0.98	0.96	**0.93**	0.99	0.98	0.96	**0.93**	1.00	1.01	0.99	0.95	0.99	0.99	0.96	0.95	0.99
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.20	1.12	1.10	1.10	1.20	1.18	1.10	1.11	1.20	1.18	1.10	1.11	1.10	1.12	1.12	1.13	1.12	**1.10**	1.13	1.12
			4	1.14	1.07	1.08	1.09	1.14	1.14	1.09	1.09	1.14	1.14	1.09	1.09	**1.04**	1.07	1.11	1.12	1.10	1.09	1.11	1.11
			8	1.03	**1.00**	1.02	1.03	1.03	1.03	1.02	1.02	1.03	1.03	1.02	1.02	1.01	**1.00**	1.02	1.03	1.02	1.04	1.02	1.03
FAR		*AVA*	2	1.07	0.96	0.96	0.96	1.07	1.03	0.97	0.98	1.07	1.03	0.97	0.98	0.97	**0.93**	0.97	0.98	0.96	0.94	0.97	0.97
			4	0.97	0.88	0.90	0.91	0.97	0.91	0.91	0.91	0.97	0.91	0.91	0.91	0.91	0.87	0.90	0.91	0.89	**0.85**	0.89	0.89
			8	0.99	0.91	0.96	0.97	0.99	0.95	0.97	0.97	0.99	0.95	0.97	0.97	1.00	0.92	0.95	0.95	1.01	**0.91**	1.01	1.01
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.22	1.11	1.14	1.13	1.20	1.18	1.14	1.13	1.20	1.15	1.14	1.13	1.11	**1.09**	1.15	1.17	1.18	1.22	1.14	1.10
			4	1.19	1.13	1.07	1.06	1.20	1.17	1.07	1.06	1.20	1.13	1.07	1.06	1.11	**1.06**	1.17	1.13	1.14	1.15	1.14	1.10
			8	1.04	1.02	**0.97**	0.99	1.06	1.03	**0.97**	0.99	1.06	1.01	**0.97**	0.99	1.06	1.14	0.98	0.99	1.02	1.05	0.99	1.00
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.05	2.41	0.94	0.94	1.07	2.64	0.94	0.95	1.07	2.76	0.94	0.95	1.04	2.42	0.99	0.97	0.94	1.96	**0.93**	0.94
			4	0.98	1.59	0.91	0.91	0.97	2.13	0.91	0.91	0.97	2.33	0.91	0.91	1.01	2.01	0.91	0.90	0.87	1.79	0.87	**0.86**
			8	1.02	2.07	0.94	0.95	1.00	2.18	0.94	0.94	1.00	2.16	0.94	0.95	0.99	2.40	**0.93**	0.96	1.02	2.25	0.97	0.97
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.12	1.14	1.13	1.10	1.12	1.14	1.10	1.10	1.12	1.14	1.10	1.10	1.24	1.12	1.11	**1.06**	1.12	1.08	1.12	1.08
			4	1.13	1.19	1.08	1.04	1.13	1.17	1.08	1.04	1.13	1.19	1.08	1.04	1.20	1.13	1.06	**1.00**	1.09	1.01	1.09	1.03
			8	0.98	1.08	0.99	0.99	0.98	1.07	0.98	0.99	0.98	1.07	0.98	0.99	1.02	1.02	**0.96**	0.98	1.03	1.05	0.98	0.99
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.06	1.76	0.96	0.94	1.06	1.68	0.96	0.94	1.06	1.75	0.96	0.94	1.21	2.17	1.00	0.95	1.00	1.44	**0.94**	0.94
			4	0.97	1.82	0.92	0.90	0.97	1.87	0.92	0.90	0.97	1.86	0.92	0.90	1.04	1.75	0.89	0.90	**0.86**	1.64	0.87	0.86
			8	0.99	2.18	0.95	0.95	0.99	1.72	0.95	0.95	0.99	1.86	0.95	0.95	1.17	2.44	**0.93**	0.93	1.01	2.07	0.98	0.97

Notes: The results show the median relative RMSE of each model and estimator made by iterated method, relative to the RMSE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. "Long Lag" stands for $p = 4$, $q = 4$, whereas "Short Lag" stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \text{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\text{UNR}_{it}, \Delta \log \text{XMKT}_{it})'$.

Table C7: Median Relative MAE for Direct Prediction Method - Consumer Price Inflation

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.00	1.02	1.03	1.00	1.01	1.03	**0.98**	1.02	1.01	1.03	1.01	1.01	1.05	1.04	1.03	1.07	1.00	0.99	1.00	1.02
			4	1.00	1.00	**0.96**	0.97	1.00	1.00	0.97	0.97	1.00	1.00	0.97	0.97	0.98	0.98	0.97	0.98	1.00	0.99	0.99	1.01
			8	1.00	1.01	1.00	1.01	1.00	1.01	1.00	1.01	1.00	1.01	1.00	1.01	1.02	0.99	**0.98**	1.01	1.00	1.00	1.00	1.01
ARDL	$\mathbf{x}_{1,it}$		2	1.02	1.01	1.02	1.00	1.01	1.01	**0.99**	1.00	1.01	1.01	1.01	1.00	1.08	1.05	1.05	1.08	1.01	1.00	1.00	1.00
			4	1.02	1.00	0.96	0.97	1.02	1.00	0.97	0.99	1.02	1.00	0.97	0.97	1.05	1.02	0.97	**0.96**	1.03	1.02	1.01	1.02
			8	1.00	0.97	0.98	0.96	1.00	0.97	0.99	0.96	1.00	0.97	0.99	0.96	1.07	1.00	0.96	**0.94**	1.01	1.00	0.98	0.96
ARDL	$\mathbf{x}_{2,it}$		2	1.02	0.98	0.99	0.97	1.00	0.98	1.00	0.97	1.00	0.98	0.99	0.97	1.05	1.02	1.01	1.06	1.02	**0.97**	0.98	1.00
			4	1.04	1.01	**0.94**	0.97	1.04	1.01	0.98	0.97	1.04	1.01	0.94	0.97	1.03	0.96	0.94	0.96	1.01	1.00	1.01	1.01
			8	1.02	0.98	0.99	0.98	1.02	0.98	0.99	0.99	1.02	0.98	0.99	0.99	1.13	1.01	1.00	1.00	1.05	1.01	1.00	**0.98**
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.12	**1.08**	1.12	1.10	1.12	1.12	1.11	1.10	1.12	1.09	1.12	1.10	1.15	1.13	1.12	1.13	1.12	1.12	1.13	1.13
			4	1.12	1.10	1.04	**1.03**	1.12	1.10	1.04	1.04	1.12	1.10	1.04	1.03	1.05	1.11	1.08	1.08	1.08	1.12	1.10	1.10
			8	1.09	1.08	1.05	1.06	1.09	1.08	1.05	1.06	1.09	1.08	1.10	1.09	**1.03**	1.08	1.05	1.05	1.06	1.06	1.08	1.08
FAR		*AVA*	2	1.03	1.00	0.98	0.98	1.03	1.02	0.99	0.99	1.03	1.02	0.98	0.99	0.96	0.97	1.01	1.02	**0.93**	0.95	0.95	0.95
			4	0.96	0.97	0.88	0.89	0.96	0.97	0.89	0.90	0.96	0.97	0.88	0.89	0.88	0.91	**0.84**	0.85	0.88	0.90	0.86	0.86
			8	1.00	0.98	0.97	0.96	1.00	0.98	0.99	0.97	1.00	0.98	0.98	0.98	0.90	0.90	0.86	**0.86**	0.92	1.00	0.96	0.96
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.18	1.16	1.09	1.08	1.18	1.19	1.10	1.08	1.18	1.19	1.09	**1.07**	1.10	1.11	1.17	1.15	1.11	1.12	1.15	1.15
			4	1.07	1.04	1.12	1.07	1.07	**0.98**	1.10	1.07	1.07	0.99	1.09	1.06	1.03	0.98	1.14	1.10	1.08	0.98	1.15	1.10
			8	1.05	1.02	1.05	1.04	1.05	1.02	1.07	1.06	1.05	**1.01**	1.06	1.05	1.08	1.19	1.09	1.07	1.01	1.03	1.07	1.05
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.03	1.51	0.94	0.93	1.03	1.42	0.95	0.96	1.03	1.48	0.94	0.95	1.06	2.48	1.01	1.02	0.93	1.91	0.92	**0.90**
			4	0.99	1.78	0.90	0.88	0.99	1.73	0.92	0.90	0.99	1.73	0.92	0.89	0.99	2.38	0.90	0.88	0.84	1.67	0.84	**0.82**
			8	1.05	1.98	0.95	0.95	1.05	1.59	0.96	0.96	1.05	1.74	0.95	0.95	0.92	2.37	0.87	**0.85**	0.97	2.22	0.93	0.93
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.14	1.15	1.11	1.09	1.14	1.15	1.11	1.11	1.14	1.15	1.11	1.08	1.21	1.09	1.09	**1.05**	1.11	1.12	1.17	1.10
			4	1.12	0.92	1.03	1.04	1.12	**0.90**	1.03	1.04	1.12	**0.90**	1.03	1.04	1.15	1.21	1.19	1.05	1.05	1.03	1.05	1.07
			8	1.01	1.00	1.05	1.03	1.01	1.00	1.06	1.06	1.01	1.00	1.04	1.04	1.03	1.20	1.08	1.04	1.03	**0.97**	1.07	1.04
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.05	1.73	0.97	0.94	1.05	1.66	0.97	0.96	1.05	1.67	0.97	0.94	1.26	2.44	1.03	1.00	0.99	1.45	**0.90**	0.91
			4	1.00	1.83	0.90	0.88	1.00	1.88	0.90	0.89	1.00	1.88	0.90	0.88	1.07	2.23	0.89	0.85	0.83	1.69	0.84	**0.82**
			8	1.01	1.86	0.95	0.95	1.01	1.71	0.95	0.96	1.01	1.82	0.95	0.96	1.06	2.83	0.89	**0.88**	1.06	2.05	0.94	0.94

Notes: The results show the median relative MAE of each model and estimator made by direct method, relative to the MAE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. “Long Lag” stands for $p = 4$, $q = 4$, whereas “Short Lag” stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \mathrm{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\mathrm{UNR}_{it}, \Delta \log \mathrm{XMKT}_{it})'$.

Table C8: Median Relative MAE for Iterated Prediction Method - Consumer Price Inflation

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.03	1.04	1.04	1.04	1.04	1.04	1.04	**0.99**	1.04	1.04	1.04	1.04	1.06	1.05	1.05	1.09	1.01	1.01	1.01	1.07
			4	0.96	0.96	0.97	0.94	0.96	0.96	0.97	0.94	0.96	0.96	0.97	0.94	1.02	1.02	1.01	1.05	**0.94**	0.95	0.95	0.98
			8	1.00	0.99	1.00	1.02	0.99	0.99	1.00	1.01	0.99	0.99	1.00	1.02	**0.99**	0.99	1.00	1.01	0.99	0.99	0.99	1.01
ARDL	$\mathbf{x}_{1,it}$		2	1.03	1.00	1.01	**0.99**	1.03	1.00	1.01	1.00	1.03	1.00	1.01	1.00	1.08	1.05	1.04	1.07	1.04	1.03	1.03	1.03
			4	0.94	0.95	0.96	**0.91**	0.94	0.95	0.96	0.92	0.94	0.95	0.96	0.92	1.03	1.02	1.01	1.00	0.96	0.96	0.96	0.93
			8	0.98	0.98	0.99	**0.95**	0.98	0.98	0.99	0.96	0.98	0.98	0.99	0.96	1.02	1.02	0.97	0.95	1.00	0.99	0.97	0.96
ARDL	$\mathbf{x}_{2,it}$		2	1.04	1.02	**0.96**	1.00	1.04	1.02	**0.96**	0.98	1.04	1.02	**0.96**	1.01	0.99	0.98	0.99	1.02	1.02	0.99	0.99	1.01
			4	0.95	0.95	**0.88**	0.94	0.95	0.95	**0.88**	0.94	0.95	0.95	**0.88**	0.94	0.98	0.95	0.96	0.96	0.94	0.95	0.95	0.95
			8	0.98	0.99	0.96	0.99	0.98	0.99	0.96	0.98	0.98	0.99	0.96	0.99	1.02	1.01	**0.95**	0.98	0.97	0.96	0.96	0.98
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.15	1.13	1.13	1.14	1.15	1.18	1.13	1.13	1.15	1.18	1.13	1.13	1.14	1.13	1.14	1.15	1.13	**1.08**	1.13	1.12
			4	1.11	1.07	**1.03**	1.04	1.11	1.12	1.04	1.05	1.11	1.12	1.04	1.05	1.07	1.07	1.08	1.08	1.07	1.06	1.08	1.08
			8	1.01	0.99	0.99	1.01	1.01	1.01	**0.98**	0.99	1.01	1.01	**0.98**	0.99	0.99	0.99	1.01	1.00	1.00	1.02	1.00	1.00
FAR		*AVA*	2	1.06	0.96	0.98	0.99	1.06	1.03	0.99	1.01	1.06	1.03	0.99	1.01	0.96	0.93	1.02	1.02	0.95	**0.93**	0.97	0.97
			4	0.96	0.91	0.89	0.89	0.96	0.92	0.90	0.91	0.96	0.92	0.90	0.91	0.89	**0.84**	0.85	0.87	0.88	0.85	0.89	0.89
			8	1.00	0.93	0.96	0.97	1.00	0.97	0.97	0.97	1.00	0.97	0.97	0.97	0.93	0.92	0.94	0.95	0.98	**0.92**	0.99	0.99
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.19	1.13	1.12	1.12	1.19	1.16	1.12	1.11	1.19	1.13	1.12	1.11	1.13	**1.09**	1.16	1.15	1.16	1.22	1.12	1.10
			4	1.18	1.16	1.10	1.08	1.21	1.14	1.10	1.08	1.21	1.13	1.10	1.08	1.13	**1.03**	1.16	1.14	1.12	1.14	1.13	1.08
			8	1.01	0.99	0.99	1.00	1.08	1.00	0.99	1.00	1.08	**0.98**	0.99	1.00	1.05	1.16	0.99	0.99	1.02	1.09	0.99	1.00
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.06	2.39	0.95	0.96	1.10	2.68	0.95	0.96	1.10	2.56	0.95	0.96	1.04	2.58	1.00	0.99	0.97	1.96	0.94	**0.93**
			4	0.98	1.67	0.90	0.89	0.98	2.06	0.90	0.89	0.98	2.29	0.90	0.89	0.97	2.12	0.89	0.86	0.88	1.94	0.86	**0.84**
			8	1.00	2.24	0.97	0.96	1.01	2.21	0.97	0.97	1.01	2.31	0.97	0.97	**0.94**	2.50	0.94	0.98	1.02	2.33	1.00	1.00
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.14	1.16	1.12	1.09	1.14	1.17	1.09	1.09	1.14	1.16	1.09	1.09	1.21	1.20	1.11	**1.07**	1.14	1.08	1.11	1.08
			4	1.10	1.17	1.12	1.05	1.10	1.18	1.10	1.05	1.10	1.17	1.10	1.05	1.21	1.08	1.06	**0.98**	1.09	1.02	1.05	1.04
			8	0.97	1.08	1.00	1.00	0.97	1.07	1.00	1.00	0.97	1.07	1.00	1.00	1.04	1.05	**0.95**	0.97	1.02	1.08	0.97	0.98
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.10	1.76	0.95	0.95	1.10	1.71	0.95	0.95	1.10	1.77	0.95	0.95	1.25	2.37	1.02	0.97	1.01	1.39	0.94	**0.94**
			4	0.97	1.86	0.92	0.88	0.97	1.88	0.92	0.88	0.97	1.97	0.92	0.88	1.00	1.65	0.85	**0.84**	0.92	1.75	0.85	0.85
			8	1.00	1.76	0.97	0.96	1.00	1.60	0.97	0.96	1.00	1.85	0.97	0.96	1.16	2.37	**0.95**	0.96	0.96	2.15	1.00	0.99

Notes: The results show the median relative MAE of each model and estimator made by iterated method, relative to the MAE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. "Long Lag" stands for $p = 4$, $q = 4$, whereas "Short Lag" stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \text{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\text{UNR}_{it}, \Delta \log \text{XMKT}_{it})'$.

Table C9: Mean Relative RMSE for Direct Prediction Method - Core Inflation

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.03	1.03	1.02	1.02	1.03	1.03	1.02	1.02	1.03	1.03	1.02	1.02	0.98	**0.98**	1.04	1.03	1.00	1.00	1.07	1.05
			4	0.98	0.97	1.05	1.02	1.07	1.07	1.05	1.02	1.07	1.07	1.05	1.02	0.98	**0.96**	1.05	1.02	1.00	1.00	1.10	1.05
			8	1.00	0.99	1.05	1.02	1.00	1.01	1.06	1.01	1.00	1.01	1.05	1.03	0.99	**0.97**	1.06	1.01	1.00	0.99	1.08	1.02
ARDL	$\mathbf{x}_{1,it}$		2	1.03	1.02	**0.98**	1.07	1.03	1.02	**0.98**	1.08	1.03	1.02	**0.98**	1.07	1.03	1.01	1.05	1.05	1.03	1.02	1.04	1.06
			4	1.05	1.01	1.00	1.07	1.05	1.04	**1.00**	1.08	1.05	1.04	1.00	1.07	1.08	1.02	1.05	1.06	1.07	1.03	1.07	1.04
			8	1.08	1.04	1.01	0.97	1.05	1.01	1.03	0.97	1.05	1.01	1.01	0.97	1.12	1.02	1.04	**0.94**	1.08	1.02	1.06	0.94
ARDL	$\mathbf{x}_{2,it}$		2	1.03	1.01	1.00	1.09	1.03	1.02	0.98	1.09	1.03	1.02	**0.98**	1.09	1.05	1.00	1.03	1.07	1.03	1.01	1.03	1.08
			4	1.01	0.97	0.98	1.08	1.05	1.03	**0.96**	1.09	1.05	1.03	0.97	1.08	1.13	1.04	1.03	1.08	1.07	1.01	1.04	1.05
			8	1.06	1.01	1.00	1.00	1.06	1.01	1.02	0.97	1.06	1.01	1.00	0.99	1.15	1.05	1.05	**0.96**	1.11	1.03	1.08	0.96
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.03	1.01	1.01	1.00	1.03	1.01	1.01	1.00	1.03	1.01	1.01	1.00	1.02	**0.97**	1.04	1.02	1.01	0.99	1.05	1.05
			4	1.07	1.03	1.04	1.01	1.08	1.04	1.03	1.02	1.08	1.04	1.03	1.02	**1.00**	1.00	1.03	1.02	1.03	1.00	1.07	1.07
			8	1.09	**1.04**	1.14	1.10	1.09	1.04	1.15	1.14	1.09	1.04	1.14	1.11	1.10	1.06	1.13	1.13	1.08	1.04	1.14	1.12
FAR		*AVA*	2	1.07	1.03	1.04	1.01	1.07	1.03	1.04	1.01	1.07	1.03	1.04	1.01	0.99	0.98	0.98	0.98	0.96	**0.96**	0.98	0.98
			4	1.14	0.98	1.07	1.03	1.15	1.08	1.06	1.04	1.15	1.08	1.07	1.04	0.98	0.99	0.97	0.97	0.95	0.96	0.96	**0.95**
			8	1.06	0.99	1.12	1.02	1.06	1.01	1.14	1.10	1.06	1.01	1.12	1.02	0.95	0.99	0.91	0.93	0.90	0.93	0.91	**0.90**
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.04	1.03	0.98	**0.96**	1.04	1.02	0.98	1.01	1.04	1.03	0.98	1.01	1.05	1.11	1.04	1.01	1.04	1.07	1.02	1.00
			4	1.05	1.10	1.02	0.97	1.05	1.06	1.01	**0.97**	1.05	1.07	1.02	0.97	1.07	1.16	1.03	1.02	1.03	1.13	1.04	0.99
			8	1.05	1.21	1.06	**0.99**	1.05	1.26	1.06	0.99	1.05	1.26	1.06	0.99	1.17	1.24	1.10	1.07	1.04	1.03	1.06	1.03
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.09	3.92	1.02	0.97	1.09	4.15	1.02	0.97	1.09	4.08	1.02	**0.97**	1.04	>5	1.01	0.99	1.01	4.94	0.98	0.97
			4	1.16	4.61	1.06	0.99	1.16	4.75	1.05	1.00	1.16	4.70	1.06	0.98	1.11	>5	1.02	1.02	1.06	>5	0.96	**0.96**
			8	1.13	3.09	1.09	1.01	1.13	3.52	1.09	1.03	1.13	3.30	1.09	1.03	1.09	>5	0.91	0.93	1.02	4.41	0.89	**0.88**
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.09	1.00	0.99	0.99	1.09	1.01	0.99	**0.98**	1.09	1.01	0.99	0.98	1.24	1.21	1.04	1.01	1.15	1.15	1.02	1.00
			4	1.08	1.10	0.97	0.94	1.08	1.11	0.98	**0.94**	1.08	1.11	0.97	0.94	1.41	1.48	1.04	0.96	1.14	1.19	1.04	0.98
			8	1.10	1.05	1.06	**0.97**	1.10	1.01	1.06	0.98	1.10	1.01	1.06	0.98	1.39	1.53	1.07	1.04	1.14	1.09	1.05	1.00
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.12	3.37	1.03	0.98	1.12	3.94	1.03	0.97	1.12	3.48	1.03	0.97	1.31	4.56	1.01	1.01	1.08	4.75	0.98	**0.96**
			4	1.16	4.56	1.00	0.97	1.16	4.80	1.02	0.96	1.16	4.80	1.00	0.96	1.46	4.54	0.99	0.99	1.09	4.74	0.99	**0.95**
			8	1.12	3.21	1.08	0.99	1.12	3.21	1.08	1.01	1.12	3.21	1.08	1.00	1.36	>5	0.91	0.93	1.08	3.43	0.89	**0.88**

Notes: The results show the mean relative RMSE of each model and estimator made by direct method, relative to the RMSE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. "Long Lag" stands for $p = 4$, $q = 4$, whereas "Short Lag" stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \text{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\text{UNR}_{it}, \Delta \log \text{XMKT}_{it})'$.

Table C10: Mean Relative RMSE for Iterated Prediction Method - Core Inflation

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.01	1.02	1.03	1.03	1.10	1.10	1.02	1.01	1.01	1.02	1.03	1.02	**1.00**	1.00	1.07	1.06	1.01	1.02	1.09	1.07
			4	1.04	1.05	1.06	1.06	1.14	1.15	1.05	1.03	1.04	1.05	1.06	1.04	1.03	**1.03**	1.13	1.11	1.04	1.05	1.15	1.12
			8	1.02	1.04	1.09	1.06	1.10	1.11	1.04	**1.01**	1.02	1.04	1.08	**1.01**	1.02	1.02	1.11	1.06	1.02	1.04	1.11	1.06
ARDL	$\mathbf{x}_{1,it}$		2	1.02	1.03	0.99	1.15	1.07	1.07	**0.98**	1.08	1.04	1.07	0.99	1.12	1.04	1.02	1.06	1.11	1.04	1.02	1.06	1.09
			4	1.05	1.03	1.00	1.23	1.09	1.08	**0.98**	1.14	1.06	1.08	1.00	1.21	1.09	1.05	1.09	1.18	1.07	1.05	1.09	1.16
			8	1.00	1.03	1.00	1.24	1.05	1.05	**0.97**	1.10	1.04	1.05	0.99	1.16	1.10	1.07	1.07	1.16	1.06	1.06	1.06	1.12
ARDL	$\mathbf{x}_{2,it}$		2	1.02	1.00	0.98	1.11	1.07	1.06	**0.98**	1.12	1.02	1.05	0.98	1.11	1.03	1.01	1.03	1.12	1.03	1.02	1.04	1.11
			4	1.04	1.02	0.99	1.18	1.10	1.08	**0.97**	1.20	1.04	1.08	0.98	1.18	1.07	1.02	1.04	1.19	1.06	1.04	1.07	1.18
			8	1.01	1.00	0.99	1.19	1.06	1.06	**0.95**	1.19	1.01	1.03	0.98	1.19	1.05	1.03	1.04	1.18	1.03	1.02	1.04	1.15
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.04	1.02	1.05	1.00	1.09	1.07	1.05	**1.00**	1.04	1.02	1.05	1.00	1.04	1.01	1.10	1.05	1.04	1.02	1.11	1.09
			4	1.09	1.06	1.10	1.02	1.15	1.12	1.09	**1.02**	1.09	1.06	1.10	1.02	1.10	1.05	1.16	1.11	1.09	1.06	1.17	1.17
			8	1.13	1.10	1.09	1.04	1.20	1.16	1.07	**1.03**	1.13	1.10	1.09	1.04	1.15	1.10	1.11	1.09	1.13	1.10	1.12	1.16
FAR		*AVA*	2	1.05	0.99	1.05	1.01	1.15	1.09	1.04	1.02	1.05	0.99	1.04	1.01	0.98	0.98	0.99	0.99	0.97	**0.97**	0.99	0.99
			4	1.09	1.00	1.08	1.04	1.19	1.11	1.07	1.04	1.09	1.00	1.08	1.04	1.01	1.02	0.99	0.99	0.97	**0.96**	0.98	0.98
			8	1.07	0.96	1.09	1.07	1.12	1.05	1.06	1.05	1.07	0.96	1.08	1.07	0.99	1.11	0.94	0.95	0.92	0.92	0.92	**0.92**
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.04	1.02	0.99	1.00	1.06	1.03	**0.99**	1.02	1.05	1.02	0.99	1.02	1.07	1.09	1.03	1.02	1.02	1.13	1.03	1.03
			4	1.07	1.08	1.01	1.01	1.08	1.05	**0.99**	1.04	1.08	1.06	1.00	1.04	1.08	1.20	1.05	1.04	1.05	1.23	1.05	1.06
			8	1.05	0.99	1.01	0.98	1.04	0.99	0.99	0.99	1.04	**0.97**	1.00	0.99	1.03	1.09	1.02	1.00	1.02	1.25	1.01	1.02
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.10	3.99	1.03	0.99	1.14	>5	1.02	0.97	1.14	4.41	1.03	0.99	1.02	>5	1.01	1.00	1.01	>5	0.98	**0.97**
			4	1.12	>5	1.05	1.00	1.15	>5	1.03	0.98	1.15	>5	1.05	0.99	1.04	>5	1.03	1.03	1.02	>5	0.97	**0.96**
			8	1.08	>5	1.06	1.00	1.10	>5	1.02	0.98	1.10	>5	1.05	1.00	1.01	>5	**0.93**	0.94	0.95	>5	0.93	0.93
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.05	1.12	1.03	0.98	1.07	1.07	1.03	**0.97**	1.06	1.10	1.03	0.97	1.25	1.18	1.10	1.00	1.09	1.12	1.09	1.02
			4	1.07	1.11	1.06	0.95	1.08	1.07	1.05	**0.95**	1.08	1.08	1.06	0.95	1.22	1.33	1.13	1.00	1.08	1.10	1.11	1.05
			8	1.02	1.02	1.07	0.96	1.03	1.02	1.06	**0.95**	1.03	1.03	1.07	0.96	1.08	1.12	1.09	0.98	1.11	1.04	1.08	1.00
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.12	4.16	1.03	0.98	1.16	4.28	1.03	0.98	1.15	4.04	1.03	0.98	1.35	4.35	1.00	1.01	1.06	4.20	1.00	**0.97**
			4	1.13	>5	1.05	0.99	1.16	>5	1.05	0.98	1.15	>5	1.05	0.99	1.41	>5	0.99	0.98	1.05	>5	0.98	**0.96**
			8	1.08	>5	1.07	1.00	1.10	>5	1.06	0.98	1.10	>5	1.07	1.00	1.17	>5	**0.93**	0.94	0.96	>5	0.94	0.93

Notes: The results show the mean relative RMSE of each model and estimator made by iterated method, relative to the RMSE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. "Long Lag" stands for $p = 4$, $q = 4$, whereas "Short Lag" stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \mathrm{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\mathrm{UNR}_{it}, \Delta \log \mathrm{XMKT}_{it})'$.

Table C11: Mean Relative MAE for Direct Prediction Method - Core Inflation

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.03	1.04	1.03	1.03	1.03	1.04	1.03	1.03	1.03	1.04	1.03	1.03	0.98	**0.97**	1.05	1.04	1.00	1.00	1.09	1.06
			4	0.97	0.98	1.08	1.04	1.07	1.09	1.08	1.04	1.07	1.09	1.08	1.04	0.97	**0.96**	1.08	1.04	1.00	1.01	1.14	1.08
			8	1.00	0.99	1.09	1.05	1.02	1.03	1.10	1.04	1.01	1.03	1.09	1.06	0.99	**0.97**	1.09	1.04	1.00	0.99	1.13	1.05
ARDL	$\mathbf{x}_{1,it}$		2	1.02	1.01	**0.97**	1.08	1.02	1.01	**0.97**	1.10	1.02	1.01	**0.97**	1.08	1.03	0.99	1.05	1.05	1.02	1.00	1.04	1.07
			4	1.05	1.01	1.02	1.10	1.04	1.03	**1.01**	1.11	1.04	1.03	1.02	1.10	1.08	1.01	1.08	1.08	1.08	1.03	1.10	1.04
			8	1.09	1.03	1.03	0.96	1.05	1.02	1.06	0.95	1.05	1.02	1.03	0.95	1.14	1.02	1.07	0.93	1.09	1.02	1.09	**0.93**
ARDL	$\mathbf{x}_{2,it}$		2	1.02	1.00	0.97	1.10	1.02	1.00	**0.96**	1.11	1.02	1.00	0.96	1.10	1.04	0.98	1.01	1.07	1.01	0.98	1.01	1.09
			4	1.00	0.95	0.98	1.10	1.03	1.01	**0.95**	1.12	1.03	1.01	0.97	1.11	1.12	1.02	1.04	1.11	1.06	1.00	1.05	1.04
			8	1.06	1.02	1.02	0.99	1.07	1.01	1.04	0.96	1.07	1.01	1.03	0.98	1.19	1.06	1.08	**0.95**	1.12	1.04	1.11	0.95
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.03	1.00	1.01	0.99	1.03	1.00	1.01	0.99	1.03	1.00	1.01	0.99	1.02	**0.96**	1.04	1.02	1.01	0.98	1.06	1.05
			4	1.10	1.04	1.07	1.04	1.10	1.05	1.06	1.04	1.10	1.05	1.06	1.04	1.00	**0.98**	1.06	1.04	1.05	1.00	1.11	1.10
			8	1.13	**1.06**	1.20	1.16	1.13	1.07	1.22	1.20	1.13	1.07	1.21	1.17	1.13	1.07	1.19	1.18	1.12	1.07	1.20	1.18
FAR		*AVA*	2	1.09	1.04	1.05	1.02	1.09	1.04	1.05	1.02	1.09	1.04	1.05	1.02	0.99	0.98	0.97	0.96	0.95	**0.95**	0.96	0.96
			4	1.18	0.97	1.11	1.06	1.19	1.10	1.10	1.07	1.19	1.10	1.10	1.06	0.96	0.97	0.96	0.96	**0.94**	0.94	0.96	0.94
			8	1.10	0.99	1.18	1.05	1.10	1.03	1.20	1.15	1.10	1.03	1.18	1.05	0.94	0.98	0.91	0.93	0.89	0.91	0.91	**0.89**
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.03	1.01	0.95	**0.93**	1.03	1.01	0.95	0.98	1.03	1.01	0.95	0.98	1.05	1.12	1.02	0.97	1.03	1.06	0.99	0.96
			4	1.03	1.10	1.03	0.96	1.03	1.06	1.01	**0.96**	1.03	1.06	1.03	0.96	1.06	1.13	1.05	1.04	1.01	1.12	1.06	0.99
			8	1.06	1.22	1.10	**1.01**	1.06	1.26	1.10	1.01	1.06	1.26	1.10	1.01	1.19	1.22	1.14	1.11	1.04	1.03	1.10	1.05
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.10	4.21	1.02	0.95	1.10	4.55	1.01	0.95	1.10	4.48	1.02	0.95	1.03	>5	0.99	0.97	0.99	>5	**0.95**	0.95
			4	1.18	>5	1.09	0.99	1.18	>5	1.08	1.00	1.18	>5	1.08	0.99	1.12	>5	1.02	1.01	1.04	>5	**0.94**	0.95
			8	1.16	3.08	1.14	1.04	1.16	3.36	1.14	1.06	1.16	3.23	1.14	1.06	1.09	>5	0.90	0.92	1.03	4.80	0.87	**0.85**
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.08	0.99	0.97	0.95	1.08	0.98	0.96	**0.95**	1.08	0.99	0.97	0.95	1.24	1.23	1.02	0.97	1.13	1.14	1.00	0.97
			4	1.07	1.11	0.97	0.92	1.07	1.11	0.98	**0.92**	1.07	1.12	0.97	0.93	1.50	1.48	1.05	0.95	1.13	1.17	1.05	0.97
			8	1.13	1.04	1.10	**0.99**	1.13	0.99	1.10	0.99	1.13	0.99	1.10	0.99	1.41	1.61	1.09	1.07	1.17	1.08	1.09	1.01
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.13	3.53	1.02	0.96	1.13	4.27	1.02	0.96	1.13	3.65	1.02	0.96	1.35	>5	0.98	0.99	1.05	>5	0.95	**0.94**
			4	1.18	>5	1.01	0.96	1.18	>5	1.04	0.95	1.18	>5	1.01	0.95	1.54	4.75	0.97	0.97	1.09	>5	0.99	**0.93**
			8	1.16	3.34	1.12	1.00	1.16	3.34	1.12	1.03	1.16	3.34	1.12	1.01	1.37	>5	0.90	0.92	1.09	3.57	0.87	**0.85**

Notes: The results show the mean relative MAE of each model and estimator made by direct method, relative to the MAE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. "Long Lag" stands for $p = 4$, $q = 4$, whereas "Short Lag" stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \mathrm{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\mathrm{UNR}_{it}, \Delta \log \mathrm{XMKT}_{it})'$.

Table C12: Mean Relative MAE for Iterated Prediction Method - Core Inflation

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.01	1.02	1.03	1.04	1.12	1.13	1.02	1.01	1.01	1.02	1.03	1.02	1.00	**1.00**	1.09	1.07	1.01	1.02	1.11	1.08
			4	1.04	1.07	1.10	1.11	1.18	1.20	1.07	1.06	1.04	1.07	1.10	1.07	**1.03**	1.03	1.17	1.16	1.04	1.07	1.20	1.17
			8	1.04	1.07	1.14	1.10	1.14	1.15	1.07	**1.03**	1.04	1.07	1.13	**1.03**	1.04	1.04	1.16	1.11	1.04	1.07	1.17	1.11
ARDL	$\mathbf{x}_{1,it}$		2	1.02	1.02	0.97	1.20	1.07	1.07	**0.96**	1.09	1.03	1.07	0.97	1.16	1.04	1.01	1.06	1.13	1.03	1.01	1.06	1.11
			4	1.04	1.03	1.01	1.32	1.11	1.10	**0.98**	1.17	1.06	1.10	1.00	1.28	1.11	1.06	1.13	1.23	1.08	1.05	1.12	1.19
			8	1.01	1.04	1.02	1.31	1.08	1.08	**0.97**	1.13	1.05	1.08	1.01	1.22	1.12	1.08	1.11	1.20	1.07	1.06	1.09	1.15
ARDL	$\mathbf{x}_{2,it}$		2	1.01	0.98	0.96	1.13	1.07	1.06	**0.95**	1.16	1.01	1.05	0.96	1.13	1.01	0.98	1.02	1.15	1.02	1.00	1.03	1.13
			4	1.03	1.00	0.99	1.24	1.11	1.10	**0.95**	1.27	1.03	1.09	0.97	1.24	1.06	1.01	1.05	1.25	1.06	1.02	1.09	1.23
			8	1.01	1.00	1.00	1.26	1.09	1.08	**0.95**	1.26	1.01	1.04	0.99	1.26	1.03	1.01	1.06	1.23	1.02	1.01	1.07	1.19
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.05	1.02	1.07	0.99	1.11	1.07	1.06	**0.99**	1.05	1.02	1.07	0.99	1.05	1.00	1.12	1.06	1.05	1.02	1.14	1.11
			4	1.13	1.08	1.14	1.05	1.22	1.17	1.12	**1.04**	1.13	1.08	1.14	1.05	1.13	1.06	1.22	1.15	1.13	1.08	1.23	1.23
			8	1.18	1.15	1.14	1.08	1.28	1.22	1.11	**1.06**	1.18	1.15	1.14	1.08	1.21	1.15	1.17	1.13	1.18	1.15	1.18	1.23
FAR		*AVA*	2	1.06	0.98	1.06	1.02	1.20	1.11	1.05	1.02	1.06	0.98	1.06	1.02	0.98	0.98	0.98	0.98	0.96	**0.95**	0.98	0.97
			4	1.12	0.99	1.12	1.07	1.25	1.16	1.10	1.07	1.12	0.99	1.12	1.07	0.97	0.99	0.98	0.97	0.94	**0.94**	0.97	0.97
			8	1.11	0.96	1.15	1.11	1.18	1.08	1.10	1.09	1.11	0.96	1.13	1.11	0.98	1.12	0.94	0.95	0.91	**0.90**	0.91	0.91
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.04	1.00	0.97	0.97	1.05	1.00	**0.97**	0.99	1.04	0.99	0.97	0.99	1.07	1.09	1.02	0.99	1.00	1.09	1.01	1.01
			4	1.08	1.04	1.02	1.01	1.07	1.02	**0.99**	1.05	1.08	1.02	1.01	1.05	1.08	1.14	1.07	1.03	1.04	1.17	1.07	1.07
			8	1.05	0.96	1.02	0.98	1.03	0.98	0.99	1.00	1.03	**0.94**	1.00	1.00	1.02	1.04	1.03	0.99	1.01	1.10	1.03	1.03
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.12	4.21	1.02	0.97	1.16	>5	1.01	0.95	1.16	4.79	1.02	0.96	1.01	>5	0.98	0.98	0.99	>5	0.95	**0.94**
			4	1.12	>5	1.08	0.99	1.17	>5	1.04	0.97	1.17	>5	1.07	0.99	1.02	>5	1.02	1.01	0.99	>5	0.95	**0.93**
			8	1.10	>5	1.10	1.00	1.12	>5	1.04	0.98	1.12	>5	1.08	1.00	0.98	>5	0.91	0.93	0.93	>5	0.90	**0.90**
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.04	1.10	1.03	0.95	1.06	1.05	1.03	**0.94**	1.06	1.08	1.03	0.94	1.23	1.16	1.10	0.97	1.07	1.08	1.09	1.00
			4	1.06	1.09	1.09	**0.94**	1.08	1.05	1.08	0.94	1.08	1.06	1.09	0.94	1.20	1.24	1.17	1.00	1.07	1.08	1.15	1.06
			8	1.01	1.00	1.11	0.96	1.04	1.02	1.10	**0.94**	1.04	1.02	1.11	0.95	1.06	1.09	1.13	0.99	1.12	1.03	1.11	1.01
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.14	4.40	1.03	0.96	1.19	4.59	1.03	0.96	1.17	4.28	1.03	0.96	1.38	4.69	0.97	0.99	1.01	4.64	0.97	**0.94**
			4	1.14	>5	1.09	0.98	1.17	>5	1.08	0.97	1.17	>5	1.09	0.99	1.45	>5	0.97	0.95	1.01	>5	0.96	**0.94**
			8	1.10	>5	1.11	1.01	1.12	>5	1.10	0.98	1.12	>5	1.11	1.00	1.17	>5	0.92	0.93	0.94	>5	0.91	**0.90**

Notes: The results show the mean relative MAE of each model and estimator made by iterated method, relative to the MAE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. "Long Lag" stands for $p = 4$, $q = 4$, whereas "Short Lag" stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \mathrm{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\mathrm{UNR}_{it}, \Delta \log \mathrm{XMKT}_{it})'$.

Table C13: Median Relative RMSE for Direct Prediction Method - Core Inflation

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.02	1.02	1.00	0.99	1.02	1.02	1.00	**0.99**	1.02	1.02	1.00	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.01
			4	0.99	0.99	1.00	**0.98**	1.04	1.05	1.00	**0.98**	1.04	1.05	1.00	**0.98**	1.00	0.98	1.00	**0.98**	1.00	1.00	1.01	0.98
			8	1.00	0.99	0.98	**0.96**	1.01	1.00	0.97	0.98	1.00	1.00	0.98	0.97	0.98	0.98	0.97	0.99	1.00	0.99	0.99	0.98
ARDL	$\mathbf{x}_{1,it}$		2	1.02	1.02	**0.96**	0.99	1.02	1.02	**0.96**	1.00	1.02	1.02	**0.96**	1.00	1.02	1.00	1.00	1.02	1.02	1.01	0.99	1.00
			4	1.01	1.01	1.01	1.03	1.03	1.01	**0.99**	0.99	1.03	1.01	1.01	1.03	1.07	1.02	1.02	1.01	1.02	1.02	1.04	1.01
			8	1.03	1.01	**0.95**	1.00	0.99	1.00	0.96	1.00	0.99	1.00	0.95	1.00	1.02	0.98	0.98	0.97	1.03	1.00	1.00	0.97
ARDL	$\mathbf{x}_{2,it}$		2	1.02	1.02	0.98	0.99	1.02	1.02	**0.96**	1.03	1.02	1.02	0.96	0.99	1.02	0.99	0.99	1.02	1.02	1.00	0.98	1.01
			4	0.98	0.97	0.99	1.02	1.02	1.02	**0.96**	1.00	1.02	1.02	0.97	1.00	1.06	1.01	1.01	1.01	1.02	1.00	1.01	1.00
			8	1.01	0.99	0.96	0.99	0.99	0.99	**0.95**	1.00	0.99	0.99	0.96	0.98	1.04	0.98	0.99	0.99	1.08	1.02	1.00	0.99
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.00	1.00	0.99	0.99	1.00	1.00	0.99	0.99	1.00	1.00	0.99	0.99	0.99	**0.98**	1.00	1.00	0.99	1.00	1.00	1.00
			4	1.05	1.01	1.01	1.02	1.06	1.02	1.00	**1.00**	1.06	1.02	1.00	1.01	1.02	1.00	1.00	**1.00**	1.02	1.01	1.00	1.00
			8	1.01	1.03	**1.00**	1.01	1.01	1.04	1.01	1.02	1.01	1.04	1.01	1.00	1.05	1.05	1.00	1.04	1.02	1.02	1.01	1.00
FAR		*AVA*	2	1.02	1.01	1.00	0.99	1.02	1.01	1.00	0.99	1.02	1.01	1.00	0.99	0.97	**0.97**	1.00	0.99	0.97	0.97	0.99	0.99
			4	1.06	1.00	1.01	1.00	1.06	1.04	1.00	0.99	1.06	1.04	1.00	1.00	**0.93**	0.97	0.94	0.93	0.97	0.96	0.98	0.98
			8	1.00	0.99	0.99	0.98	1.00	1.00	1.01	1.00	1.00	1.00	1.00	0.97	0.97	1.02	**0.88**	0.94	0.96	0.93	0.94	0.92
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.00	1.00	0.97	0.96	1.00	0.97	0.96	0.97	1.00	1.00	0.97	0.97	1.02	0.99	0.97	0.97	1.01	1.03	0.97	**0.96**
			4	1.03	0.99	1.00	**0.94**	1.03	0.97	1.00	0.94	1.03	0.99	1.01	0.94	1.06	1.08	1.00	1.00	1.03	0.97	1.02	0.96
			8	0.99	1.17	0.98	**0.94**	0.99	1.19	0.99	0.96	0.99	1.19	0.99	0.95	1.09	1.10	0.99	1.02	1.02	0.98	0.99	0.99
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.04	2.95	0.99	0.96	1.04	3.07	0.99	0.96	1.04	3.08	0.99	0.96	1.01	3.66	0.99	0.96	0.98	3.94	0.97	**0.92**
			4	1.11	3.22	1.05	0.97	1.11	3.30	1.02	0.99	1.11	3.08	1.04	0.98	1.05	3.85	0.98	0.99	1.05	3.44	0.95	**0.89**
			8	1.03	2.12	1.00	0.96	1.03	2.18	1.00	0.98	1.03	2.28	1.00	0.98	1.02	4.26	0.83	0.89	1.10	2.18	0.88	**0.81**
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.04	0.97	0.98	0.96	1.04	0.98	0.97	**0.95**	1.04	0.98	0.98	0.95	1.20	1.12	0.99	0.97	1.13	1.07	0.97	0.95
			4	1.08	1.03	0.97	0.91	1.08	1.05	0.98	**0.90**	1.08	1.03	0.97	0.91	1.22	1.25	1.04	0.94	1.10	1.08	1.01	0.94
			8	0.98	0.95	0.98	**0.93**	0.98	0.94	0.98	0.95	0.98	0.94	0.98	0.95	1.18	1.31	0.99	0.99	1.10	1.05	0.96	0.96
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.07	2.49	0.99	0.95	1.07	2.62	0.99	0.96	1.07	2.56	0.99	0.95	1.19	3.32	1.00	0.98	1.06	3.91	0.98	**0.95**
			4	1.13	3.58	1.00	0.96	1.13	3.28	1.00	0.96	1.13	3.28	1.00	0.95	1.28	2.67	0.99	1.00	1.08	3.44	0.98	**0.92**
			8	1.02	1.97	0.99	0.96	1.02	1.97	0.99	0.97	1.02	1.97	0.99	0.96	1.23	2.75	0.84	0.90	1.18	2.24	0.90	**0.81**

Notes: The results show the median relative RMSE of each model and estimator made by direct method, relative to the RMSE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. "Long Lag" stands for $p = 4$, $q = 4$, whereas "Short Lag" stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \text{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\text{UNR}_{it}, \Delta \log \text{XMKT}_{it})'$.

Table C14: Median Relative RMSE for Iterated Prediction Method - Core Inflation

				AIC				*BIC*				*HQ*				*Long Lag*				*Short Lag*			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.00	1.01	0.99	0.99	1.04	1.05	1.00	0.98	1.00	1.01	0.99	**0.98**	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.01
			4	1.01	1.03	1.01	1.01	1.06	1.06	1.00	0.99	1.01	1.03	1.00	**0.98**	1.01	1.02	1.04	1.01	1.01	1.03	1.04	1.02
			8	1.00	1.00	1.00	0.99	1.01	1.01	**0.97**	1.00	1.00	1.00	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.01	1.00
ARDL	$\mathbf{x}_{1,it}$		2	1.02	1.03	0.97	0.99	1.05	1.06	**0.96**	1.00	1.03	1.06	0.97	0.98	1.01	1.01	1.01	1.02	1.02	1.03	1.01	1.01
			4	1.04	1.02	0.99	1.02	1.06	1.06	**0.98**	1.03	1.05	1.06	0.99	1.04	1.04	1.03	1.04	1.03	1.06	1.05	1.04	1.03
			8	0.98	0.99	0.97	1.04	0.99	0.99	**0.96**	1.01	0.99	0.99	0.96	1.00	0.98	0.99	1.01	1.01	1.01	1.02	0.98	1.01
ARDL	$\mathbf{x}_{2,it}$		2	1.01	1.00	0.96	1.02	1.06	1.06	**0.95**	1.04	1.01	1.05	0.96	1.02	1.01	1.00	0.98	1.02	1.01	1.01	1.00	1.01
			4	1.03	1.00	0.98	0.99	1.06	1.06	**0.96**	1.04	1.03	1.06	0.97	0.99	1.01	1.01	1.00	1.03	1.05	1.04	1.03	1.03
			8	0.98	0.99	0.97	1.00	1.01	1.01	0.95	1.01	0.98	0.99	**0.95**	1.00	0.98	1.00	0.99	1.00	1.00	1.02	0.97	1.01
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.01	1.01	1.00	**0.99**	1.02	1.02	1.01	0.99	1.01	1.01	1.00	**0.99**	1.00	1.00	1.02	1.00	1.01	1.01	1.03	1.01
			4	1.04	1.05	1.01	**1.00**	1.03	1.04	1.00	1.00	1.04	1.05	1.01	**1.00**	1.05	1.04	1.05	1.04	1.04	1.05	1.06	1.04
			8	1.05	1.05	1.00	0.98	1.08	1.07	0.99	**0.97**	1.05	1.05	1.00	0.98	1.08	1.05	1.00	1.00	1.05	1.05	1.01	1.04
FAR		*AVA*	2	1.02	0.98	1.00	0.99	1.08	1.01	0.99	0.99	1.02	0.98	1.00	0.99	**0.95**	0.95	1.01	1.00	0.96	0.97	0.99	0.99
			4	1.04	0.98	1.00	0.99	1.06	1.01	1.00	0.99	1.04	0.98	1.00	0.99	0.96	0.97	1.00	0.99	0.97	**0.94**	0.99	0.99
			8	1.00	0.97	1.00	0.98	1.01	0.99	0.98	0.98	1.00	0.97	0.99	0.98	1.01	1.00	**0.86**	0.87	0.98	0.97	0.97	0.97
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.01	1.03	0.98	**0.95**	1.00	1.03	0.96	0.98	1.00	1.01	0.98	0.98	1.07	1.06	0.96	0.96	0.99	1.03	0.97	0.99
			4	1.04	1.01	1.01	**0.98**	1.03	1.00	1.00	1.01	1.03	1.02	1.01	1.01	1.06	1.11	1.04	1.02	1.03	1.09	1.04	1.02
			8	1.00	0.99	0.94	0.94	0.98	0.97	0.95	0.95	0.98	**0.92**	0.94	0.95	0.98	1.00	0.96	0.97	0.96	0.98	0.96	0.96
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.05	2.77	1.00	0.97	1.10	2.94	1.00	0.95	1.10	2.80	1.00	0.97	1.02	>5	1.01	0.99	0.98	2.91	0.97	**0.95**
			4	1.10	2.82	1.04	1.00	1.12	3.02	1.01	0.97	1.12	2.54	1.04	0.99	1.05	3.96	1.01	0.96	1.00	2.95	0.95	**0.92**
			8	1.04	2.95	0.98	0.96	1.04	2.71	0.98	0.97	1.04	2.43	0.97	0.96	0.92	3.76	0.84	**0.81**	0.96	2.93	0.93	0.92
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.01	1.10	1.00	0.97	1.02	1.02	1.00	0.95	1.03	1.04	1.00	0.96	1.17	1.13	1.04	**0.95**	1.05	1.02	1.04	0.98
			4	1.03	1.06	1.05	0.96	1.02	1.05	1.05	**0.95**	1.04	1.08	1.05	0.95	1.11	1.07	1.08	0.96	1.05	1.06	1.06	1.02
			8	0.97	0.98	0.98	0.94	0.98	0.97	0.97	0.95	0.98	1.00	0.98	**0.93**	1.02	1.00	1.00	0.94	1.08	1.00	0.99	0.95
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.09	3.50	1.00	0.96	1.15	3.80	1.00	**0.95**	1.11	3.01	1.00	0.96	1.32	3.16	1.00	1.00	0.99	3.00	0.99	0.96
			4	1.10	3.62	1.05	0.98	1.13	3.27	1.05	0.98	1.12	3.79	1.05	0.98	1.20	3.96	0.98	0.95	0.98	4.00	0.97	**0.93**
			8	1.04	3.13	0.98	0.96	1.04	3.52	0.97	0.97	1.04	3.29	0.98	0.96	0.97	4.99	0.88	**0.82**	0.99	4.02	0.92	0.92

Notes: The results show the median relative RMSE of each model and estimator made by iterated method, relative to the RMSE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. "Long Lag" stands for $p = 4$, $q = 4$, whereas "Short Lag" stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \mathrm{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\mathrm{UNR}_{it}, \Delta \log \mathrm{XMKT}_{it})'$.

Table C15: Median Relative MAE for Direct Prediction Method - Core Inflation

				AIC				BIC				HQ				Long Lag				Short Lag			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.02	1.02	1.00	0.98	1.02	1.02	1.00	0.97	1.02	1.02	1.00	0.98	0.99	0.99	0.99	**0.97**	1.00	1.00	1.01	1.00
			4	1.00	0.99	1.01	**0.98**	1.04	1.04	1.01	**0.98**	1.04	1.04	1.00	**0.98**	1.00	0.98	1.01	**0.98**	1.00	1.00	1.01	0.98
			8	1.00	0.99	0.97	0.95	1.01	1.01	0.96	0.95	1.01	1.01	0.97	0.95	0.99	0.97	0.96	0.95	1.00	0.98	0.98	**0.94**
ARDL	$\mathbf{x}_{1,it}$		2	1.03	1.01	**0.95**	1.02	1.03	1.01	**0.95**	0.99	1.03	1.01	**0.95**	1.02	1.02	1.00	1.00	1.00	1.01	1.00	0.99	0.99
			4	1.00	1.00	1.01	1.00	1.03	1.01	**0.97**	0.97	1.03	1.01	1.01	1.00	1.04	1.00	1.04	1.00	1.03	1.01	1.05	0.99
			8	1.02	1.00	0.95	0.96	1.00	0.98	0.95	0.95	1.00	0.98	0.95	0.96	1.02	0.96	0.95	0.97	1.02	1.00	0.96	**0.95**
ARDL	$\mathbf{x}_{2,it}$		2	1.03	1.01	0.96	1.01	1.03	1.01	**0.95**	1.01	1.03	1.01	0.95	1.01	1.02	0.98	0.99	0.98	1.02	0.99	0.98	0.99
			4	0.97	0.96	0.98	1.00	1.01	1.00	**0.93**	0.99	1.01	1.00	0.96	0.98	1.01	0.97	1.03	1.00	0.98	0.98	1.01	0.95
			8	1.02	1.00	0.94	0.96	1.01	0.98	**0.94**	0.95	1.01	0.98	0.94	0.94	1.07	0.97	0.96	0.97	1.04	1.00	0.96	0.95
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	0.99	0.98	0.98	0.98	0.99	0.98	0.98	0.98	0.99	0.98	0.98	0.98	1.00	**0.98**	0.98	0.98	1.00	0.99	0.99	0.99
			4	1.05	1.01	1.02	1.01	1.06	1.01	1.01	1.01	1.06	1.01	1.01	1.01	1.02	**0.99**	1.01	1.01	1.03	1.02	1.00	1.00
			8	1.02	1.04	**0.99**	1.02	1.02	1.04	1.02	1.01	1.02	1.04	0.99	1.00	1.06	1.06	1.01	1.03	1.03	1.04	1.00	1.00
FAR		*AVA*	2	1.02	1.02	0.99	0.99	1.02	1.02	0.99	0.99	1.02	1.02	0.99	0.99	1.00	**0.96**	1.02	1.01	0.97	0.99	0.99	0.99
			4	1.07	0.99	1.02	1.01	1.07	1.05	1.01	1.01	1.07	1.05	1.01	1.01	**0.90**	0.92	0.95	0.94	0.97	0.94	0.97	0.97
			8	1.00	0.98	0.97	0.95	1.00	1.01	1.01	1.00	1.00	1.01	0.98	0.96	0.92	0.97	**0.88**	0.89	0.95	0.94	0.93	0.92
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	0.99	0.99	0.93	0.92	0.99	0.98	0.94	0.95	0.99	0.99	0.93	0.95	1.01	1.06	0.97	0.94	1.03	1.03	0.95	**0.92**
			4	0.98	1.00	0.98	0.94	0.98	0.93	0.98	**0.92**	0.98	0.94	1.01	0.93	1.00	0.99	1.03	1.00	0.97	0.96	1.01	0.95
			8	0.95	1.14	0.97	**0.93**	0.95	1.14	0.95	0.94	0.95	1.14	0.95	0.95	1.09	1.08	0.99	1.02	1.01	0.99	0.97	0.97
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.03	3.17	0.98	0.94	1.03	3.05	0.98	0.95	1.03	3.04	0.98	0.94	1.03	3.78	1.01	0.95	0.99	4.50	0.92	**0.89**
			4	1.13	3.83	1.05	0.96	1.13	3.54	1.04	0.96	1.13	3.58	1.05	0.96	1.03	3.83	0.99	0.95	1.02	3.47	0.94	**0.93**
			8	1.04	2.34	0.99	0.95	1.04	2.21	0.99	0.97	1.04	2.35	0.99	0.97	0.94	4.71	0.91	0.91	1.04	2.29	0.86	**0.81**
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	1.08	0.96	0.94	0.93	1.08	0.95	0.94	**0.92**	1.08	0.97	0.94	0.92	1.25	1.12	0.96	0.95	1.15	1.06	0.96	0.94
			4	1.06	0.99	0.94	**0.89**	1.06	1.00	0.95	0.91	1.06	0.99	0.94	0.90	1.28	1.33	1.03	0.93	1.06	1.02	1.01	0.92
			8	0.99	0.95	0.95	0.93	0.99	0.93	0.95	0.93	0.99	0.93	0.95	**0.93**	1.17	1.36	0.95	1.00	1.10	1.02	0.96	0.96
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.05	2.64	0.97	0.94	1.05	2.74	0.97	0.95	1.05	2.61	0.97	0.95	1.32	3.30	1.00	1.00	1.05	4.57	0.92	**0.90**
			4	1.09	3.89	0.98	0.98	1.09	3.54	1.00	**0.93**	1.09	3.54	0.98	0.94	1.29	2.83	0.95	0.98	1.08	3.04	0.96	0.95
			8	1.03	2.05	0.97	0.93	1.03	2.05	0.97	0.95	1.03	2.05	0.97	0.95	1.23	2.76	0.87	0.89	1.11	2.40	0.90	**0.80**

Notes: The results show the median relative MAE of each model and estimator made by direct method, relative to the MAE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. "Long Lag" stands for $p = 4$, $q = 4$, whereas "Short Lag" stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \mathrm{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\mathrm{UNR}_{it}, \Delta \log \mathrm{XMKT}_{it})'$.

Table C16: Median Relative MAE for Iterated Prediction Method - Core Inflation

				AIC				BIC				HQ				Long Lag				Short Lag			
Model	*Predictors*	*Method*	*Horizon*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*	*OLS*	*GLS*	*FE*	*MG*
AR			2	1.01	1.01	1.00	0.99	1.04	1.05	0.98	**0.96**	1.01	1.01	1.00	0.97	1.00	1.00	1.02	1.00	1.01	1.01	1.01	1.00
			4	1.01	1.02	1.01	0.99	1.06	1.06	1.00	**0.96**	1.01	1.02	1.02	0.97	1.01	1.01	1.02	1.01	1.01	1.02	1.04	1.01
			8	1.00	0.99	0.98	0.96	1.01	1.01	**0.95**	0.97	1.00	0.99	0.97	0.97	0.97	0.99	1.00	0.97	1.00	0.99	1.00	0.97
ARDL	$\mathbf{x}_{1,it}$		2	1.03	1.01	0.96	1.02	1.04	1.04	**0.95**	0.97	1.01	1.04	0.97	1.00	1.01	0.99	1.01	1.00	1.04	1.03	1.01	1.00
			4	1.03	1.00	0.96	1.05	1.05	1.05	**0.95**	1.00	1.03	1.05	0.96	1.02	1.02	1.04	1.04	1.02	1.05	1.05	1.07	1.02
			8	0.96	0.97	0.94	1.05	0.97	0.98	0.95	0.99	0.96	0.98	**0.94**	1.00	0.99	0.99	0.97	1.01	0.99	0.98	0.96	1.01
ARDL	$\mathbf{x}_{2,it}$		2	1.01	0.99	**0.94**	1.01	1.06	1.04	0.95	1.03	1.01	1.03	0.95	1.01	1.01	0.98	0.97	1.00	1.03	1.01	1.00	1.01
			4	1.00	0.99	0.95	1.03	1.05	1.06	**0.93**	1.01	1.00	1.05	0.94	1.03	1.00	1.01	1.01	1.01	1.04	1.03	1.05	1.02
			8	0.96	0.96	**0.93**	1.03	0.99	0.99	0.95	1.03	0.96	0.97	0.94	1.03	0.97	1.00	0.96	1.00	1.00	0.99	0.96	1.00
				CCE	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*	*CCE*	*IPC*	*CCEP*	*IPCP*
FAR		*RBA*	2	1.01	1.02	1.00	0.98	1.02	1.00	0.99	**0.98**	1.01	1.02	1.00	0.98	1.00	1.00	1.01	0.99	1.01	1.02	1.02	1.01
			4	1.06	1.06	1.02	**1.01**	1.04	1.05	1.01	1.01	1.06	1.06	1.02	**1.01**	1.08	1.06	1.05	1.03	1.06	1.06	1.05	1.05
			8	1.06	1.06	0.99	0.98	1.10	1.10	0.97	**0.97**	1.06	1.06	0.99	0.98	1.09	1.08	1.00	0.99	1.06	1.06	1.00	1.05
FAR		*AVA*	2	1.02	0.98	0.99	0.99	1.06	1.01	0.99	0.99	1.02	0.98	0.99	0.99	0.97	**0.96**	1.01	1.02	0.98	0.97	0.99	0.99
			4	1.02	0.98	1.03	1.00	1.07	1.00	1.01	1.01	1.02	0.98	1.03	1.00	0.98	1.00	0.99	0.99	0.95	**0.93**	0.96	0.97
			8	1.00	0.97	1.00	0.97	1.01	0.98	0.97	0.97	1.00	0.97	0.99	0.97	1.00	1.02	**0.93**	0.96	0.98	0.95	0.97	0.97
FARDL	$\mathbf{x}_{1,it}$	*RBA*	2	1.01	1.04	0.94	0.95	1.01	1.01	**0.93**	0.95	1.01	1.01	0.93	0.95	1.06	1.02	0.96	0.95	0.98	1.00	0.96	0.96
			4	1.03	0.99	1.00	0.96	0.98	0.96	0.96	0.99	1.00	1.00	**0.95**	0.99	1.06	1.02	1.01	0.99	1.02	1.07	1.02	1.00
			8	0.96	0.95	0.93	0.91	0.93	0.96	0.94	0.92	0.93	**0.91**	0.92	0.92	0.96	0.91	0.92	0.94	0.94	0.95	0.92	0.93
FARDL	$\mathbf{x}_{1,it}$	*AVA*	2	1.04	2.56	0.98	0.97	1.08	3.30	0.97	0.94	1.08	2.66	0.99	0.96	1.02	>5	1.01	1.00	0.98	2.91	0.92	**0.91**
			4	1.08	2.78	1.04	0.97	1.10	3.36	1.01	0.95	1.10	2.80	1.04	0.96	1.01	4.12	0.97	0.95	0.97	3.31	**0.93**	0.93
			8	1.02	2.57	0.98	0.96	1.04	2.74	0.98	0.98	1.04	2.16	0.98	0.97	0.88	3.94	**0.88**	0.93	0.95	3.11	0.90	0.90
FARDL	$\mathbf{x}_{2,it}$	*RBA*	2	0.99	1.09	0.97	0.93	1.01	1.02	0.98	0.94	1.01	1.02	0.97	0.93	1.19	1.05	1.02	**0.92**	1.05	1.06	1.04	0.97
			4	0.99	1.06	1.04	**0.92**	0.97	1.01	1.04	0.93	0.99	1.07	1.04	0.94	1.13	1.05	1.09	0.96	1.02	1.04	1.06	1.00
			8	0.94	0.95	0.99	0.92	0.96	0.98	0.98	0.93	0.96	0.97	0.99	0.92	1.06	1.00	1.00	0.92	1.03	0.98	0.99	**0.92**
FARDL	$\mathbf{x}_{2,it}$	*AVA*	2	1.07	3.18	0.97	0.96	1.11	3.40	0.98	0.95	1.11	3.11	0.97	0.96	1.43	2.88	0.97	1.00	0.99	3.75	0.93	**0.91**
			4	1.08	3.98	1.04	0.96	1.13	3.57	1.04	0.95	1.11	4.10	1.04	0.96	1.21	3.90	0.98	0.97	0.97	4.19	0.95	**0.93**
			8	1.04	3.23	0.99	0.95	1.03	3.42	0.98	0.97	1.03	3.47	0.99	0.94	0.98	4.80	0.88	0.93	0.95	3.80	**0.88**	0.90

Notes: The results show the median relative MAE of each model and estimator made by iterated method, relative to the MAE of the forecasts made by an AR(2) model using direct method. Minimum value in each row is shown in bold. "Long Lag" stands for $p = 4$, $q = 4$, whereas "Short Lag" stands for $p = 2$, $q = 2$, whenever applicable. The vector of external predictors are set as $\mathbf{x}_{1,it} = \text{UNR}_{it}$ and $\mathbf{x}_{2,it} = (\text{UNR}_{it}, \Delta \log \text{XMKT}_{it})'$.

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Dépendance Inter-Individuelle sur Panels Hétérogènes :
Estimation, Inférence et Prévision

La disponibilité de données de panel ayant des dimensions temporelle et individuelle comparables et importantes augmente rapidement. Cette structure offre de nouvelles perspectives pour appréhender et caractériser les dépendances inter-individuelles. Cette thèse, tout en s'appuyant sur la littérature récente liée aux panels hétérogènes de grande taille en présence de dépendances inter-individuelles, en propose trois prolongements. Le premier chapitre traite des problèmes d'estimation, d'inférence et de prévision, en se concentrant sur la comparaison d'estimateurs hétérogènes, homogènes et partiellement homogènes en présence de dépendances inter-individuelles. Ces dernières renvoient à des structures de dépendance spatiale sur les perturbations et à la présence de facteurs communs. Le deuxième chapitre se focalise sur l'élaboration de tests robustes à différentes structures de dépendance inter-individuelle afin d'évaluer la qualité prédictive de plusieurs panels. Enfin, le troisième chapitre se concentre sur les prévisions, obtenues sur la base d'approches itérée et directe, et l'introduction de termes spécifiques liés aux dépendances inter-individuelles dans les prédicteurs. La comparaison des prévisions de taux d'inflation sur un panel de pays de l'OCDE révèle notamment l'importance de la prise en compte des facteurs communs.

Mots-clés : Dépendance Inter-Individuelle, Evaluation des Prévisions, Facteurs Communs, Tests d'Hypothèses, Panel Spatial.

Cross-Sectional Dependence in Heterogeneous Panels:
Estimation, Inference and Forecasting

The availability of panel data sets with comparable and large time and individual dimensions is rapidly increasing. This structure offers new possibilities to understand and characterize cross-sectional dependence. This thesis makes three contributions to the recent literature dealing with large heterogeneous panel data sets with cross-sectional dependence. The first chapter deals with estimation, inference and forecasting issues focusing on the comparison of heterogeneous, homogeneous and partially homogeneous panel data estimators in presence of cross-sectional dependence modeled by spatial error dependence and common factors. In the second chapter novel tests for equal predictive ability in panels of forecasts are proposed, allowing for different types and strength of cross-sectional dependence across units. Finally, the third chapter focuses on forecasts obtained using iterated and direct methods. A special emphasis is put on the predictors which contain terms related to interactions between panel units. Inflation forecasts for the OECD countries are compared empirically. The results show the importance of taking common factors into account to predict inflation.

Keywords: Common Factors, Cross-Sectional Dependence, Forecast Evaluation, Hypothesis Testing, Spatial Panels.