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Transferts internationaux, stabilité politique et développement économique au Moyen-Orient, en Afrique du Nord et en Afrique sub-saharienne.

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Résumé

Cette thèse examine les interactions complexes entre les différents flux financiers vers les pays en développement (les investissements directs étrangers (IDE), l’Aide Publique et les transferts personnels) d’un côté, la croissance économique, les indicateurs de gouvernance et l'économie informelle d’un autre côté dans plusieurs zones géographiques. Le premier chapitre relève que les IDE et la stabilité politique sont des moteurs mutuels de la croissance du PIB, avec des variations régionales remarquables, suggérant que les contextes socio-politiques ont un impact significatif sur cette relation. Notamment, les investissements directs étrangers associés à la stabilité politique pourraient encourager une croissance durable. En étendant cette analyse, le deuxième chapitre met en évidence un cercle vertueux où la croissance économique et une diminution de la corruption attirent l'aide étrangère et les transferts de fonds, ce qui entraîne en retour une croissance et une diminution de la corruption. Cependant, il semble que cette relation dynamique diffère entre l'Afrique subsaharienne, le Moyen-Orient et l'Afrique du Nord, ce qui souligne l'influence des structures économiques et politiques sous-jacentes. Le troisième chapitre porte sur l'économie informelle, soulignant que les transferts personnels (« remittances ») et la stabilité politique sont des facteurs clés influençant sa taille, mais avec des effets à court terme principalement. Les analyses révèlent que les transferts de fonds pourraient être principalement axés vers la satisfaction des besoins immédiats plutôt que vers des investissements à long terme, une tendance observée dans les différentes économies, y compris celles de l'OCDE.

Ces chapitres soulignent l'importance de considérer les interdépendances dynamiques entre les transferts financiers, la stabilité politique ainsi que les pratiques économiques à la fois formelles et informelles, et comment ces facteurs se renforcent mutuellement pour influencer les trajectoires de développement économique.

Descripteurs : IDE, Aide publique, Aides personnelles, Indicateurs de gouvernance, Secteur informelle

Abstract

This thesis examines the complex interactions between different financial flows to developing countries (Foreign Direct Investments (FDI), Public Aid, and personal transfers) on one side, and economic growth, governance indicators, and the informal economy on the other side across several geographic areas. The first chapter finds that FDI and political stability are mutual drivers of GDP growth, with remarkable regional variations, suggesting that socio-political contexts significantly impact this relationship. Notably, foreign direct investments coupled with political stability could encourage sustainable growth. Extending this analysis, the second chapter highlights a virtuous circle where economic growth and a reduction in corruption attract foreign aid and fund transfers, which in turn lead to growth and reduced corruption. However, this dynamic relationship appears to differ between Sub-Saharan Africa, the Middle East, and North Africa, underscoring the influence of divergent economic and political structures. The third chapter focuses on the informal economy, pointing out that remittances and political stability are key factors influencing its size, but with short-term effects. The analyses reveal that fund transfers are possibly geared towards immediate needs rather than long-term investments, a trend observed in various economies, including those of the OECD. These chapters underscore the importance of considering the dynamics between financial transfers, political stability, and both formal and informal economic practices, and how these factors mutually reinforce each other to influence economic development trajectories.

Keywords: FDI, Public Aid, Remittances, Governance Indicators, Informal Sector

Principales abréviations

FDI : Foreign Direct Investment

IDE : Investissement direct à l'étranger

MENA Region : Middle East and North Africa Region

SSA : Sub-Saharan Africa

OECD : The Organisation for Economic Co-operation and Development

OCDE: Organisation de Coopération et de Développement Économiques

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0. Thèse de Doctorat

0.1. Introduction générale de la thèse

Cette thèse explore les interactions contemporaines entre pays développés et pays en développement ou sous-développés. Ces interactions, principalement financières liées à l'Investissement Direct à l'étranger (IDE) et l'Aide Publique au Développement, sont influencées ou stimulées par divers facteurs économiques, politiques et sociaux dans les pays bénéficiaires.

Notre première partie de l'analyse (chapitre 1 et 2) étudie les relations entre les divers facteurs cités ci-dessus, défini les interactions ainsi que le sens de la causalité le cas échéant. Les deux régions utilisées pour notre étude comparative sont le Moyen et l'Afrique Sub-Saharienne.

Cette étude fournit des explications sur les différences de comportement et de stratégies entre donateurs et bénéficiaires. Ces deux zones géographiques partagent de nombreux facteurs susceptibles d'affecter la stabilité politique. Cependant, elles diffèrent en termes de régimes politiques ainsi que de composition de leur richesse nationale.

L'IDE est devenu un élément essentiel à étudier dans les économies modernes, particulièrement avec l'ouverture croissante des économies mondiales. Des facteurs internes tels que la stabilité politique et la croissance économique peuvent influencer l'IDE. Bien que plusieurs études utilisant le test de causalité de Granger aient examiné les liens entre l'IDE, la stabilité politique et la croissance économique, peu se sont intéressées à la région du Moyen-Orient et de l'Afrique du Nord (MENA), et aucune n'a effectué de comparaison entre la région MENA et d'autres régions, telles que l'Afrique. Notre analyse comparative entre la région MENA et plusieurs pays africains contribue à la littérature existante en expliquant les disparités de comportement et de stratégies entre les donateurs et les bénéficiaires, malgré les nombreux facteurs communs pouvant affecter la stabilité politique dans ces régions, qui diffèrent cependant dans leurs régimes politiques et la composition de leur richesse nationale.

D'autre part, la communauté internationale joue un rôle actif et significatif pour aider les nations en développement à surmonter les effets de diverses crises, telles que les catastrophes politiques, économiques ou environnementales. Les agences internationales telles que la Banque mondiale, le Fonds monétaire international (FMI) et les Nations Unies (ONU) sont souvent les principales sources de ces flux financiers, catégorisés sous l'appellation d'Aide Publique au Développement. L'intérêt pour ce sujet a augmenté au cours des dernières décennies, marquées par de nombreuses crises économiques et politiques majeures ainsi que des catastrophes humanitaires. En plus des entrées financières officielles, les nations touchées peuvent recevoir des paiements personnels ou des transferts de fonds de la part de résidents de la diaspora qui maintiennent des liens étroits avec leur famille dans leur pays d'origine. Ces transferts financiers varient en type et forme, selon les situations économiques, sociales et politiques des pays bénéficiaires. Dans cette étude, nous analysons l'impact et la corrélation entre ces facteurs, et tentons d'établir les relations de causalité (au sens de Granger-Sims) propres à la région MENA et à l'Afrique subsaharienne.

Le troisième chapitre de notre analyse inclut, en plus des facteurs déjà cités, l'économie informelle et son impact sur les flux financiers concernés. En outre, les pays de l'OCDE et ceux de l'Amérique Latine sont également intégrés à nos régions étudiées, ce qui nous permet d'élargir notre échantillon à quatre zones géopolitiques différentes.

Cette dernière partie de la thèse étudie la relation entre l'économie informelle, la stabilité politique et les « remittances » en utilisant un modèle P-VAR (Panel Vector Auto-Regressive Model). Une étude comparative entre quatre zones géographiques a été menée, le Moyen-Orient/Afrique du Nord (MENA) et l'Afrique subsaharienne (SSA), l'Amérique latine ainsi que les pays de l'Organisation de Coopération et de Développement Economiques (OCDE). Un test de causalité de Granger a été utilisé pour identifier la direction de causalité dominante. Les résultats indiquent que les « remittances » sont positivement corrélées à la taille du secteur informel à court terme dans les quatre régions.

0.2. Méthodologie

Notre première partie de recherche (chapitres 1 et 2) examine les relations entre les Investissements Directs Etrangers (IDE), l'Aide Publique au Développement, la croissance économique et la stabilité politique en utilisant un panel de données couvrant 32 pays d'Afrique subsaharienne et du Moyen-Orient, recueillies entre 2002 et 2017.

Les données proviennent de la Banque Mondiale, complétées par des informations de l'IMF, des Nations Unies et de l'OCDE.

Les variables analysées incluent l'IDE, le PIB, la stabilité politique, les remittances, l'aide publique au développement ainsi que la corruption.

Pour analyser ces données, nous avons normalisé les valeurs en utilisant les logarithmes des IDE, de l'Aide Publique et des remittances. Nous avons également standardisé les indicateurs de gouvernance pour une analyse plus précise.

Afin de traiter les problèmes de causalité potentiels, nous avons employé le modèle PVAR (Panel Vector Auto-regressive Model), bien adapté pour traiter les interdépendances statiques et dynamiques, ainsi que la variation temporelle des coefficients et la variance des chocs.

Les hypothèses économétriques testées concernent les relations de causalité entre l'IDE, le PIB et la stabilité politique, ainsi qu'entre l'Aide Publique, les remittances, le PIB et la corruption. Nous avons utilisé le test de causalité de Granger pour identifier les relations de causalité et déterminer le décalage optimal dans nos modèles, avec un focus particulier sur les décalages d'un an qui se sont révélés être les plus pertinents pour plusieurs régressions.

Les résultats préliminaires indiquent des corrélations possibles entre ces variables ainsi qu'avec leurs propres valeurs décalées. L'analyse a été approfondie à l'aide du modèle PVAR avec la méthode des moments généralisés (GMM Estimation), exploitant toutes les conditions d'orthogonalité entre les variables dépendantes décalées et le terme d'erreur.

Cette approche méthodologique nous permet de saisir à la fois les dynamiques à court terme et les relations à long terme entre les flux financiers internationaux et les variables politico-économiques dans les régions étudiées, offrant une compréhension nuancée des forces à l'œuvre.

Dans notre deuxième partie de recherche (chapitre 3), centrée sur le secteur informel, nous avons adopté des méthodologies supplémentaires en plus de celles utilisées dans la première partie (chapitres 1 et 2). Nous avons notamment intégré l'approche MIMIC (Multiple Indicators Multiple Causes).

Cette approche est utilisée pour estimer la taille de l'économie informelle en considérant plusieurs causes et effets de ce secteur. Ce modèle comprend un modèle structurel, qui lie des variables causales exogènes à une variable latente (la taille de l'économie informelle), et un modèle de mesure qui associe cette variable latente à des indicateurs observables. Cette méthode permet de capturer les interactions complexes entre les causes observables et les manifestations de l'économie informelle.

Comme indiqué ci-dessus, nous avons également utilisé le modèle PVAR et le test de causalité de Granger pour analyser les données de 1996 à 2017 pour divers ensembles géopolitiques incluant le MENA, l'Afrique subsaharienne, l'Amérique Latine et les pays de l'OCDE. Ces modèles permettent d'aborder des questions de causalité en observant les interdépendances statiques et dynamiques entre les variables telles que les remittances, le PIB, la stabilité politique et le secteur informel. Le modèle PVAR est particulièrement adapté pour traiter la variation temporelle et l'hétérogénéité dynamique entre les pays.

Dans les deux parties de nos recherches (chapitre 1, 2 et 3) des tests de colinéarité et de stationnarité ont été effectués pour assurer la fiabilité des données temporelles. Des analyses de la fonction de réponse impulsionnelle (IRF) et de la décomposition de la variance des erreurs de prévision (FEVD) ont également été conduites pour renforcer la robustesse des résultats. Ces analyses sont détaillées dans les annexes de la thèse.

L'analyse a inclus la recherche d'un décalage optimal pour le modèle, avec des critères basés sur des indicateurs comme le MBIC, MAIC, et MQIC, permettant d'optimiser les tests de causalité selon les ensembles géopolitiques étudiés.

Cette méthodologie intégrée permet une compréhension approfondie et robuste des dynamiques de l'économie informelle et de son interaction avec d'autres facteurs économiques et politiques au niveau international.

Pour résumer, les principales méthodes utilisées dans nos recherches sont le modèle PVAR (Panel Vector Auto-regressive Model), le test de causalité de Granger, l'approche MIMIC, la méthode des moments généralisés (GMM) ainsi que des tests de robustesse statistique et économétrique.

0.3. Résultats principaux

Dans le premier chapitre, nous avons utilisé un modèle VAR en panel pour examiner les relations entre le PIB, l'investissement direct étranger (IDE) et un indicateur de stabilité politique (PS). En utilisant le test de causalité de Granger, nous avons trouvé que le PIB est fortement influencé par sa propre valeur retardée d'un an, indiquant une forte autocorrélation. L'IDE est positivement corrélé avec le PIB, ce qui démontre que l'IDE cause (au sens de Granger) une augmentation du PIB. Cependant, la stabilité politique, prise séparément, ne semble pas augmenter le PIB.

En considérant conjointement l'IDE et la stabilité politique, il est apparu que leur variation commune à un impact positif sur le PIB des pays bénéficiaires. Nous avons aussi observé que la stabilité politique peut être causée par les IDE, indiquant que les flux d'IDE vers un pays peuvent améliorer sa stabilité politique.

Une analyse comparative entre les régions du Moyen-Orient et de l'Afrique sub-saharienne a révélé que les relations de causalité sont ambiguës dans les échantillons incluant uniquement les pays du Moyen-Orient, probablement en raison de l'hétérogénéité politique et sociale de ces pays. En revanche, en Afrique, l'IDE et la stabilité politique peuvent conjointement et séparément causer une augmentation du PIB.

Dans le deuxième chapitre, nous avons exploré les relations entre l'Aide Publique au Développement, la croissance du PIB ainsi que la corruption en utilisant également un modèle VAR en panel. L'analyse a montré que la croissance du PIB peut engendrer une augmentation de l'Aide Publique, particulièrement si le pays bénéficiaire montre une gouvernance efficace et une croissance économique.

Dans la région MENA, nous avons constaté que la croissance économique, couplée à une amélioration de l'indice de corruption, peut attirer à la fois l'Aide Publique au développement et les remittances. Cette dynamique crée un cercle vertueux où l'amélioration des politiques attire plus d'aides et d'investissements, qui à leur tour stimulent davantage la croissance et réduisent la corruption.

L'analyse a également souligné l'importance des remittances, qui, lorsqu'elles sont utilisées efficacement, peuvent contribuer à augmenter le PIB à long terme en finançant des projets qui soutiennent l'activité économique.

Ces synthèses reflètent les interactions complexes et les dynamiques économiques examinées dans nos analyses, mettant en lumière l'impact significatif de l'IDE et de la stabilité politique sur la croissance économique, ainsi que le rôle potentiel de l'Aide Publique au Développement et des remittances dans le développement économique dans les pays récipients.

Dans notre deuxième partie de recherche (chapitre 3), les résultats montrent une corrélation significative entre les variables étudiées, notamment les remittances, la taille du secteur informel et la stabilité politique dans les quatre zones géographique étudiées. Au Moyen Orient et en Afrique Sub-Saharienne nous observons un effet à court terme ainsi qu'à long terme.

Dans le premier cas, une corrélation positive existe entre les transferts de fonds et l'expansion du secteur informel. Les transferts de fonds semblent encourager la croissance de ce secteur, probablement en raison de leur utilisation dans des activités non déclarées. Cependant, la stabilité politique n'a pas d'effet direct sur le secteur informel. Dans le deuxième cas, si les transferts de fonds continuent à influencer la taille du secteur informel à court terme, leur impact combiné avec la stabilité politique diminue avec le temps. Cela suggère que les transferts sont principalement utilisés pour répondre à des besoins immédiats plutôt que pour investir dans des entreprises formelles ou informelles à long terme.

En Amérique Latine, il existe à court terme, une relation bidirectionnelle entre les transferts de fonds et le secteur informel, chaque variable influençant l'autre. La stabilité politique n'affecte pas directement le secteur informel mais influence indirectement les transferts de fonds. Les relations causales à court terme dominent, tandis que les effets à long terme sont limités. Des recherches supplémentaires sont nécessaires pour mieux comprendre ces dynamiques et élaborer des politiques adaptées.

Dans les pays de l'OCDE, les remittances influencent positivement, à court terme, la taille du secteur informel, et il existe une interaction complexe avec la stabilité politique. Toutefois, à long terme, l'influence de la stabilité politique diminue. Contrairement aux pays en développement, où le secteur informel est une nécessité, dans les pays de l'OCDE, il pourrait s'agir de choix stratégiques. Il est important d'adapter les politiques pour gérer ces particularités régionales.

Dans les pays où les remittances représentent une part importante du PIB, ces fonds jouent un rôle essentiel dans la croissance du secteur informel. Toutefois, la stabilité politique ne semble pas influencer directement ce secteur ni les flux des remittances.

En résumé, les remittances ont un impact significatif, mais souvent de courte durée, sur le secteur informel, et leur interaction avec la stabilité politique varie en fonction du contexte régional. Ces conclusions offrent des pistes pour des interventions politiques et des recherches futures visant à promouvoir la croissance économique tout en prenant en compte les particularités locales.

0.4. Chapitre 1 Investissement Direct Étranger, PIB et Stabilité Politique : relations causales ou variables indépendantes ? Etude économétrique de la région MENA et de l'Afrique Subsaharienne

Le chapitre 1 examine la relation entre les investissements directs étrangers (IDE) et le produit intérieur brut (PIB). Cette analyse se déroule parallèlement à l'étude de la stabilité politique dans les économies bénéficiaires des pays en développement. Dans ce chapitre, nous avons étudié la corrélation entre ces variables et la manière dont d'autres facteurs et variables peuvent les affecter ou les stimuler. Dans notre recherche, nous avons utilisé le test de causalité de Granger pour détecter la causalité entre les variables présentées dans notre modèle. Nous avons ensuite testé la multicolinéarité en calculant le facteur d'inflation de la variance correspondant associée. Nous avons constaté que ce facteur n'affectait pas le modèle. Les résultats ont démontré que le PIB et la stabilité politique pourraient être causés, au sens de Granger, par les IDE. Les résultats ont montré que seule l'augmentation des IDE et l'augmentation de la stabilité politique dans les pays bénéficiaires peuvent impacter positivement le PIB. Toutefois, l'augmentation de la stabilité politique quant à elle, n'est pas suffisante pour stimuler le PIB en tant que variable distincte. Nous avons également constaté que l'augmentation conjointe du PIB et des IDE peut conduire à assurer une stabilité politique plus importante. Ces résultats peuvent varier entre le Moyen-Orient et l'Afrique subsaharienne, les deux régions de notre modèle. Cela peut être dû aux différences dans les déterminants sociaux et politiques des deux régions.

0.5. Chapitre 2 Aide Publique au développement, Transferts Personnels de Fonds, PIB et Corruption : Variables indépendantes ou interdépendantes dans les pays en développement ? Etude économétrique de la région MENA et de l'Afrique Subsaharienne

Dans cette deuxième étude, nous avons analysé la relation entre les principales variables économiques et statistiques qui lient les pays développés et en développement sur le plan économique et politique. Nous avons effectué une analyse empirique et des tests statistiques en utilisant le Modèle Autorégressif Vectoriel (VAR) ainsi que le test de causalité de Granger. Ces techniques ont révélé un cercle vertueux intéressant et dynamique de relations causales entre l'aide étrangère, les envois personnels de fonds (« remittances »), la croissance et la corruption. Il est notable que les modèles VAR prennent explicitement en compte les structures de cointégration des variables. De plus, les décompositions de la variance de l'erreur de prévision ou les réponses aux chocs sont généralement utilisées pour examiner les interactions dynamiques entre les variables.
Nos résultats montrent que la croissance combinée à une amélioration de l'indice de corruption, ce qui signifie une réduction de la corruption, pourrait attirer l'aide étrangère et les envois de fonds, ce qui à son tour pourrait avoir un effet positif en augmentant la croissance et en diminuant la corruption. Ainsi, nous pourrions observer une relation complémentaire entre ces différentes variables contrairement à celles indiquées par plusieurs autres articles de recherche. Nous mettons en évidence un cercle vertueux dynamique de ce type dans la région du Moyen-Orient et de l'Afrique du Nord. Cependant, la même analyse empirique et les mêmes tests statistiques n'ont pas produit de résultats comparables dans la région de l'Afrique subsaharienne.

0.6. Chapitre 3 Secteur Informel, Transferts personnels de Fonds et Stabilité Politique : Une étude de la causalité de Granger dans quatre grands ensembles géopolitiques

Le troisième chapitre étudie la relation entre l'économie informelle, la stabilité politique et les remittances en utilisant un modèle P-VAR (Panel Vector Auto-Regressive). Une étude comparative entre quatre régions du monde – le Moyen-Orient/Afrique du Nord (MENA) et l'Afrique subsaharienne (SSA), l'Amérique latine et les pays de l'Organisation de Coopération et de Développement Economique~~s~~ (OCDE) – a été menée, ainsi qu'un test de causalité de Granger pour déterminer quelle direction de causalité prédomine. Nous avons trouvé une corrélation significative entre ces variables. Dans les quatre régions, les résultats montrent une corrélation positive entre les « rémittances » et la taille du secteur informel à court terme. Nous avons constaté que les transferts personnels de fonds causent le secteur informel au sens de Granger. En tant que variable séparée, la stabilité politique n'a pas de relation causale avec le secteur informel. Cependant, les transferts personnels de fonds et la stabilité politique considérés ensemble causent le secteur informel au sens de Granger. Nous n'avons pas trouvé de résultat significatif lorsque nous avons effectué notre test pour le moyen et le long terme pour la région du MENA, l'Afrique Sub-Saharienne et l'Amérique latine. Nous concluons que l'effet de ces deux variables n'est que de court terme. Cela pourrait signifier que les transferts de fonds sont investis dans des besoins initiaux plutôt que dans des investissements formels ou informels. Lorsque nous avons effectué notre test à moyen et long terme, nous avons trouvé des résultats significatifs pour les pays de l'OCDE.

Nous observons également que la stabilité politique cause les transferts personnels de fonds au sens de Granger d'une part et que le secteur informel et les « rémittances » causent la stabilité politique au sens de Granger ensemble et séparément d'autre part.

1. Chapter 1: Foreign Direct Investment, GDP and Political Stability: causal relationships or independent variables ? Evidence from MENA Region and Sub-Saharan Africa

1.1. Abstract

This paper investigates the relationship between foreign direct investment (FDI) and gross domestic product (GDP). This analysis takes place in parallel with studying political stability in recipient economies. In this paper, we studied the correlation between these variables and how other factors and variables may affect or stimulate them. In our research, we used the Granger causality test to detect the causality between the variables presented in our model. We then tested for multicollinearity by computing the associated corresponding variance inflation factor. We found that this factor did not affect the model. The results demonstrated that GDP and political stability could be Granger-caused by FDI. The results showed that only both increasing FDI and increasing political stability in recipient countries can increase GDP. However, an increase in political stability as a separate factor is not sufficient to stimulate GDP on its own. We also found that increasing GDP and FDI jointly can lead to greater political stability. These results may vary between the Middle East, and sub-Saharan Africa, the two regions in our model. This is due to differences in the social and political determinants of both regions.

Keywords: Political stability, Governance indicators, Foreign direct investment, Quality of government, Trade liberalisation.

1.2. Introduction Chapter 1

Foreign direct investment (FDI) has become an important factor to study in modern economies with the increasing degree of openness in economies around the world. A variety of internal factors can affect FDI, such as political stability and economic growth. There are several Granger causality test studies about the relationships between FDI, political stability and economic growth. However, only a few of them treated this subject in the Middle East and North Africa (MENA) region, and there are no comparative studies between the MENA region and other regions, such as Africa. For this reason, we contribute to the literature by undertaking a comparative analysis between the MENA region and several African countries. This comparative study provides explanations for the differences in behaviour and strategies between donors and recipients. These two regions have many factors in common that can affect political stability. However, they differ in their political regimes as well as in the composition of their national wealth.

In this study, we noticed a significant correlation between our main variables. The positive correlation between FDI and GDP is clear, but introducing the political stability factor could affect this result. Our results showed that GDP could Granger-cause FDI in the short run. However, in the context of growing political instability, GDP alone is not sufficient to attract FDI. Moreover, FDI and increasing political stability, taken together, Granger-cause GDP in the short run. Further, Kurecic and Kokotovic (2017) showed that there is a long-term relationship between political stability and FDI for a panel of small economies, yet we did not find the same long-term relationship in our panel. Also, Lucas (1990) and Kurecic and Kokotovic (2017) argued that FDI outflows tend to go to less politically stable countries.

Kurecic and Kokotovic (2017) used three different panels of countries. The first panel contains 11 very small economies, the second includes five well-developed and politically stable economies with highly positive FDI net inflows, and the third is a panel with economies that are prone to political violence or targeted by terrorist attacks. They found a long-term relationship between political stability and FDI for the panel of small economies. This relationship arose from the fact that FDI outflows tend to go directly to less stable countries. They also found no empirical evidence of such a relationship for panels of larger and more developed economies. Moreover, they found a long-term relationship between FDI and political stability, whereas our own study only found a medium-term relationship between these two variables. FDI also Granger-caused increasing political stability in our African subsample. For this reason, we applied the Granger causality test to detect the effects of the political stability variable. The political stability factor and its consequences are key factors to study, especially in regions and zones with a significant political instability.

The common finding in the MENA region and sub-Saharan Africa is that an increase in the GDP of the recipient country can be Granger-caused by a combination of FDI and a good level of political stability. An important difference between the two regions is the ongoing relationships among GDP, FDI, and political stability. In the sub-Saharan African sample, our result presented a dynamic cycle of causality: FDI Granger-causes increases in GDP as well as political stability, which in turn improve GDP in the recipient country. This dynamic circle did not occur in the sample of the Middle Eastern countries. Therefore, our study shows that the impacts of FDI can be different between the African region and the Middle East. FDI Granger-causes increases in GDP and political stability in African countries, but it does not have the same effect in the MENA region. More generally, most of the literature concludes that FDI is the engine of growth (Adeniyi et al., 2015; Alzaidy et al., 2017; Begum et al., 2018; Caesar et al., 2018; Chowdhury, 2016; Faisal et al., 2016; Nwaogu & Michael, 2015; Soleimani et al., 2016; Simionescu, 2016). Our results concur with the reviewed literature with respect to the African panel, but not with respect to the Middle Eastern one.

As mentioned above, the growth of GDP can have a significant role in attracting FDI. Almfraji and Almsafir (2014) concluded that most papers suggest that there is a positive relationship between FDI and economic growth. Our results join these studies with a similar outcome, but more precisely that FDI Granger-causes GDP increases in African countries. Mehrara et al. (2010) used a panel data approach with a sample of 57 developing countries. They found a short-run causality from FDI net inflows and exports on GDP. However, in our model, FDI Granger-causes the GDP increases *only when* an amelioration of political stability takes place. In other words, one cannot neglect the political stability factor, at least in a medium-run period.

Jenkins and Thomas (2002) argued that abroad subsidiaries will be identified by resource seeking-investors to insure a more stable or cheaper supply of inputs, as raw materials and energy sources as well as factors of production. Ngowi (2001) showed that many developing countries attract little FDI because many consider them high risk and [they] are characterized by a lack of political and institutional stability and predictability. At this stage, our results show that FDI can also improve political stability in the recipient countries—primarily in the African sample.

1.3. Africa and the Middle East

Many studies have analysed the relationship between foreign aid and FDI. These studies explore the correlation between these transfers in relation with several factors in the recipient countries. However, our contribution to this body of literature is to show this relationship with regard to variables like political stability in sub-Saharan Africa as well as the MENA region. In addition, we examine this relationship in areas with different levels of political instability in the recipient countries according to the World Bank.

Hassan (2017) studied FDI flows to the Middle East region over a period of 35 years (1981–2015). He found that purchasing power, human capital, and trade openness are the key determinants of inward FDI inflows for the growth and development of the Middle East region. In our study, we found that a good political situation combined with FDI could increase GDP in recipient countries, whether in the MENA region or in sub-Saharan Africa. Olusanya (2013) studied the relationship between FDI and economic growth by using the Granger causality test. He compared the context of the pre- and post-deregulated Nigerian economy. He found that economic growth drove foreign direct investment into the country in the second period. Mallaye and Yogo (2011) used cross-country panel data from 33 fragile states in Africa, they showed that foreign aid is complementary to remittances and FDI. They found that the level of GDP could affect this relationship.

Frimpong and Oteng-Abayie (2006) used the Granger causality method to study the causality direction between FDI and economic growth in Ghana. They found that there is no causality between FDI and growth for the total sample period and the pre-Structural Adjustment Program period. FDI, however, caused GDP growth during the post-Structural Adjustment Period, which is consistent with our finding in this last point. We suggest that the judicious selection of projects related to foreign aid can improve the state of infrastructure in parallel with implementing other policies and rules in affect other governance factors and decrease corruption, which will in turn lead to receiving higher FDI inflows.

Chan and Gemayel (2004) found that the degree of instability in investment risk is a much more critical determinant of foreign investment in countries in the MENA region than it is for developing countries, which have lower levels of investment risk. Our study shows that the situation could be different between the African region and the Middle East. FDI Granger causes GDP and political stability in African countries, while this is not the case in the Middle East.

Lucas (1990) showed that only political risk is an important factor that affects capital inflows. He found that less stable countries could attract more FDI than stabler ones, while we found that an improvement of political stability could positively affect FDI. Also, Musibah (2017) found that in MENA region, political stability plays a major role in attracting FDI unlike monarchy states countries, where political stability plays a lesser role. He also indicates that with the increasing political instability, FDI decreases.

The political stability factor could play a different role depending on the studied region. For instance, our results showed that FDI has a negative response to political instability in sub-Saharan Africa, while in the Middle East, the effects remain unclear. At this stage, politicians of recipient countries must play an important role and demonstrate considered efforts to attract foreign capital. Onyeiwu (2003) analysed the determinants of FDI in Middle Eastern countries. He studied economic growth next to other determinants of FDI and showed that it was not as significant in the Middle Eastern case as in other developing countries. The results of our model concur in this reflection by showing that the situation in the Middle East is significantly different from the situation in developing countries in other regions. He found that only trade openness and corruption have a significant effect on FDI in the Middle East. Therefore, his study showed that trade liberalisation and privatisation contribute positively more than macroeconomic stabilisation strategies in determining FDI inflows to the Middle East.

1.4. Model and Data Description

To answer the questions expounded above, we built a panel of 32 sub-Saharan African and Middle Eastern countries that are known for being relatively politically unstable. This dataset covers the period between 2002 and 2017. We collected our data from the World Bank Data (DataBank), knowing that several variables came from the IMF, the United Nations Population Fund and the OECD. The variables we used are Foreign direct investment, GDP, Political stability.

In our database, we applied standard methods of retreatment to the data to facilitate econometric analyses. As a first step, we normalized the data by using logarithmic values of FDI. Then, we worked on the governance indicators by using standardised values to make an accurate analysis. To observe the political stability in the recipient countries and to check the relationships between variables and the effects of the different transfers during the political stability/instability, we used the World Bank indicator, political stability and absence of violence. This indicator ranges from –2.5 to 2.5, from the worst situation to the best situation. With our dataset, we used random-effects GLS regression to check the relationships among the three types of donors and the relationships with the internal factors in the recipient countries.

Furthermore, it seemed that our model might be suffering from causality issues, so we used the vector autoregressive (VAR) model, more specifically the panel VAR model, which is compatible with our dataset considering the repeated time values. The panel VAR model seems particularly well suited to address issues that are currently at the centre of discussion in academia and in the policy arena since it can (a) capture both static and dynamic interdependencies, (b) treat the links across units in an unrestricted fashion, (c) easily incorporate time variation in the coefficients and in the variance of the shocks and (d) take cross-sectional dynamic heterogeneities into account. The panel VAR model was run with the generalised method of moments, which exploits all the orthogonality conditions between the dependent lagged variables and the error term.

We used econometric analysis to investigate the following three prior hypotheses relating to the relationships among our three variables of interest, namely FDI, GDP and political stability.

Hypothesis 1: FDI inflows are high if political stability and GDP are relatively high.

Hypothesis 2: Political stability is enhanced by a high level of FDI and GDP.

Hypothesis 3: GDP is increased by an increasing FDI inflow and an improvement in political stability.

The preliminary results of our panel VAR model showed that our variables could be correlated together, as well as the possibility that they may correlate with their own lagged values. To resolve this issue, we used the Granger causality test to try to detect, understand and define the causality issues better. In addition, we checked the optimal lag in our model by presenting lags over several years. By using the panel VAR model and the Granger causality test, we showed that a lag of only 1 year is the optimal choice in several regressions.

The bivariate Granger Causality test involves regressing the respective index on m-lag values of the index and m-lag values of the reference index.

$$Y_t = \sum Y_{t-i} + \sum X_{t-i}$$

$$X_t = \sum X_{t-i} + \sum Y_{t-i}$$

$$Y_{i,t} = \alpha_{0,i} + \alpha_{1,1} Y_{i,t-1} + \cdots + \alpha_{1,i} Y_{1,t-1} + \beta_{1,i} X_{i,t-1} + \cdots + \beta_{1,i} X_{1,-1} + \cdots + \varepsilon_{i,t},$$

$$X_{i,t} = \alpha_{0,i} + \alpha_{1,1} X_{i,t-1} + \cdots + \alpha_{1,i} X_{1,t-1} + \beta_{1,i} Y_{i,t-1} + \cdots + \beta_{1,i} Y_{1,-1} + \cdots + \varepsilon_{i,t},$$

The null hypothesis that the reference index does not Granger-cause the chosen index is accepted if and only if no lagged values of reference are retained in the regression. An F-test is then used to determine whether the coefficients of m-lag of the reference index are jointly equal to zero. The p-values for each F-test are presented in table format.

$$FDI_t = \alpha_0 + \alpha_1 FDI_{t-1} + \cdots + \alpha_{1,2} FDI_{t-n} + \alpha_2 GDP_{t-1} + \cdots + \alpha_{2,1} GDP_{t-n} + \alpha_3 PS_{t-1} + \cdots + \alpha_{3,1} PS_{t-n} + \gamma_4 C_t$$

$$GDP_t = \beta_0 + \beta_1 GDP_{t-1} + \cdots + \beta_{1,2} GDP_{t-n} + \beta_2 FDI_{t-1} + \cdots + \beta_{2,1} FDI_{t-n} + \beta_3 PS_{t-1} + \cdots + \beta_{3,1} PS_{t-n} + \gamma_4 C_t$$

$$PS_t = \gamma_0 + \gamma_1 PS_{t-1} + \cdots + \gamma_{1,2} PS_{t-n} + \gamma_2 GDP_{t-1} + \cdots + \gamma_{2,1} GDP_{t-n} + \gamma_3 logFDI_{t-1} + \cdots + \gamma_{3,1} PS_{t-n} + \gamma_4 C_t$$

where FDI is the log of foreign direct investment, GDP is the log of real GDP, PS is a variable that accounts for political stability and absence of violence/terrorism, C is an exogenous control variable; α_1..4, β_1..4, γ_1..4 are coefficients and α_0, β_0, γ_0 are constants.

1.5. Results

1.5.1. Granger Causality Test

To check the relationships among our variables, we proceeded by running several regressions using our panel VAR model against the complete sample. We used the Granger causality test to check which variable is causing the other variables. We based our analyses on two hypotheses:

- ❖ *Panel VAR-Granger causality Wald test*
  - *If H_0 is verified: Excluded variable does not Granger-cause equation variable*
  - *If H_a is verified: Excluded variable Granger-causes equation variable*

Furthermore, we ran a regression for the whole sample to check the causality between GDP, FDI and PS indicator. We found that GDP is correlated with its own lagged value by 1 year. This means that the GDP in year N highly affects the GDP of the year N + 1. In addition, we found that FDI is positively correlated with GDP. Table 1.3 presents the results of the Granger causality test. This shows that FDI Granger-causes the increase in GDP. However, political stability, taken as a separate variable, does not increase GDP. If we consider the variation of political stability and FDI jointly, we find that the variation of both factors positively causes the GDP of the recipient countries.

Next, we examined reverse causality. The results showed that political stability and GDP do not cause FDI. Then, we checked how political stability could be caused. We noticed that GDP as a separated factor does not affect or cause political stability in the developing countries of our sample. However, we noticed that FDI inflows were strongly correlated with GDP and political stability. The results showed that the FDI indicator could cause political stability in recipient countries. We should mention here that a common variation of FDI and GDP could affect and cause positive political stability in the recipient countries. This means that a good level of GDP is not sufficient to keep or increase political stability in recipient countries. However, a common increase of the GDP rate along with FDI could help to keep or improve political stability. For this reason, we can show that GDP and FDI have a complementary role vis-à-vis the political stability indicator.

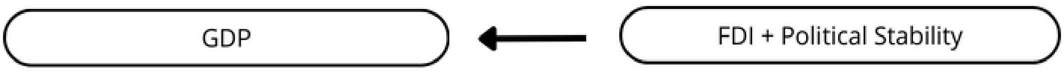
1.5.2. Comparative Analysis Results

In this section, we report a comparative analysis between the Middle East region and the African countries in our panel. We found that the causality relationships are ambiguous in the sample that includes only the Middle Eastern countries (table 1.4). This might be explained by heterogeneity of the Middle Eastern countries. Differences between the political and social regimes could be the reason for the ambiguity of the causality-test results. In the Middle East, political stability/instability could have different effects on the economic schemes of various countries. For instance, political instability could be more easily controlled in monarchies, while in more democratic regimes, this could be less easy to control. Therefore, the effects of such political stability/instability could vary between different countries in the Middle East.

The common point between the Middle East region and sub-Saharan Africa is that GDP of the recipient country could be Granger-caused by a joint effect of the FDI and a good level of political stability. A dynamic circle of correlation and causality is defined by using the African sample. The FDI Granger-causes the GDP as well as the political stability, which in turn improves the GDP in the recipient country. This dynamic circle is not observed in the sample of the Middle Eastern countries (Figures 1.1 and 1.2).

Figure 1.1

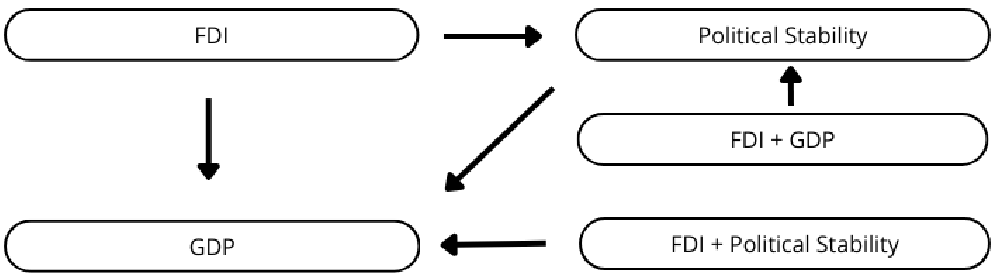
Causal Interactions: Middle East Countries



Alternatively, by using the African countries on our panel, we found that FDI and Political Stability could cause GDP, jointly and separately (Table 1.5). We also found that FDI could positively affect political stability. The scheme in the African countries is different from that in the Middle Eastern ones. In Africa, foreign countries could be interested in implementing their business, taking account of the wealth and the potential of the African continent. The causal relationship between FDI and the political stability might be explained by the fact that the foreign countries could contribute to creating an acceptable political stability situation in these countries, which will help to implement business and transfer funds for investments.

Figure 1.2

Causal Interactions: African Countries



1.5.3. Collinearity Test Results

Figure 1.2 shows the results of the several regressions we performed. The diagram shows the interactions between the variables for FDI, GDP and political stability. In the upper part of the diagram, we report the interactions between the variables considered separately. In the lower part of the diagram, we report the direction of causality. Concerning the joint interactions in the lower part of the diagram, we performed a complementary test of robustness of the causality relationship by evaluating the degree of collinearity of the independent variables of the regression.

In the first case (left lower part of the diagram), the GDP is the dependent variable, and FDI and political stability are the independent (Granger-causing) variables. The joint variation of FDI and political stability Granger-causes GDP. We tested the collinearity between FDI and political stability by computing the associated corresponding variance inflation factor (VIF, see the appendix). Table 1.14 displays a VIF of 1. With that result and according to the standard rule of thumb for VIF (see the appendix), this direction of causality is not jeopardised by collinearity issues and appears, therefore, robust in this respect. In the second case (right lower part of the diagram), political stability is the dependent variable, and FDI and the GDP are the independent (Granger-causing) variables. Table 1.15 displays a VIF of 11.27, meaning that the FDI and the GDP variables are highly correlated. Joint Granger-causality appears less robust in this case in this respect.

Finally, we know that using a lagged value of several variables is important to see the causality issues more clearly. That is why we searched for the optimal lag value for our model. Table 3 shows that the optimal lag to use in our model is 1 year with the smallest MBIC, MAIC and MQIC as it minimises Hansen's *p*-value. We refer here to Andrews and Lu's (2001) selection criterion.

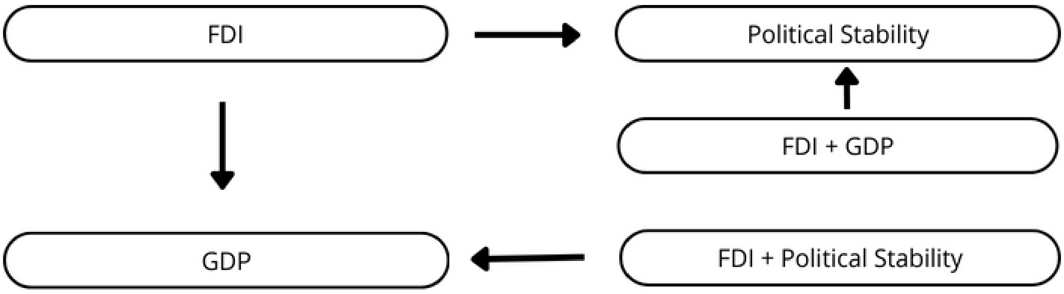
1.5.4. Group Countries Analysis Results

Furthermore, we can analyse a country group, which includes countries from the Middle East and Africa that have strong common causality relationships. These relationships are explainable by the fact that the more stable the country is, the more this country can attract FDI. In such countries, a stable political environment is necessary to increase FDI inflows. This selected country group comprises Algeria, Benin, Burundi, Central African Republic, Lebanon, Iraq, Somalia and Sudan.

Figure 1.3 shows our results for the whole sample of countries. This presentation is very close to the diagram of the African sample (Figure 1.2). The single difference lies in the fact that in the whole sample, political stability does not Granger-cause improved GDP. However, in the African sample it does increase GDP in recipient countries. This means that the political situation in the Middle East is very heterogenous between different countries, consistent with the fact that we can find democratic and monarchical regimes in the same region, while both the political regimes and the social factors are more homogenous in the African countries.

Figure 1.3

Causal Interactions for the Whole Panel



1.6. Conclusion

This study has clarified some aspects of the complex relationships between FDI, GDP and political stability in the MENA region and of a sample of sub-Saharan countries. Based on our data, we show that FDI is highly correlated with political stability and GDP, but it is not caused by both factors in the whole sample. This stands in sharp contrast with Lucas (1990), who, notably, argued that only political risk is an important factor affecting capital inflows. This is probably due to differences in the dataset and the studied period. Our results lead us to highlight the importance of GDP and FDI in maintaining political stability in the studied group of countries. FDI and political stability are considered jointly as important factors to stimulate GDP.

In addition, we have completed a comparative study between two contrasting subsets of our sample of countries. The first is the Middle East region, and the second is sub-Saharan African countries. This study has led us to distinguish different causality types operating in these two regions. This leads us to conclude that we cannot generalise a result or a hypothesis if we do not consider the political and sociological circumstances of each region.

The common finding between the Middle East region and sub-Saharan Africa is that the GDP of the recipient country can be Granger-caused by a joint effect of FDI and a good level of political stability. However, in the African sample, our result presents a dynamic cycle of causality. The FDI Granger-causes the GDP as well as the political stability, which in turn improves the GDP in the recipient country. This dynamic cycle is not replicated in the sample of the Middle Eastern countries. The causality relationships in the Middle East remain ambiguous, while the causality relationships among variables are better confirmed in the African countries. This might be due to the homogeneity of the political regimes and the sociological factors among the African countries and the relative heterogeneity among Middle Eastern ones.

This study contributes to the literature by explaining the significant similarities and differences between the countries of these two different regions. Our results are similar to other studies, such as those by Almfraji and Almsafir (2014), who concluded that most papers suggest that there is a positive relationship between FDI and economic growth. Our results join with this body of literature. While Lucas (1990) found that less stable countries could attract more FDI than more stable ones, we found that an increase in political stability could positively affect FDI. Therefore, governments and policymakers—especially in developing and underdeveloped countries—must keep one eye on the importance of political stability in their nations and the other eye on their GDP indicators while they are implementing their policies.

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2. Chapter 2: Public Foreign Aid, Remittances, GDP and Corruption: Independent or interdependant variables in developing countries ? Evidence from MENA Region and Sub-Saharan Africa

2.1. Abstract

This paper explores the multifaceted relationships between foreign aid, economic growth, corruption, and remittances within the Middle East and North Africa (MENA) and Sub-Saharan Africa regions, both significantly affected by various crises. We specifically analyze how political and economic transfers can preemptively mitigate the effects of crises or support recovery. Using panel vector autoregression (Panel VAR) models and Granger causality tests, our study assesses the interactions between GDP growth and foreign aid, highlighting the influence of increasing GDP on attracting more aid in Sub-Saharan Africa and MENA regions. In the MENA region we observe a dynamic complementarity between aid and remittances in fostering economic development and reducing corruption. This suggests that foreign aid and remittances not only co-evolve but also reinforce each other to enhance economic growth and improve governance in recipient countries. Our empirical analysis leverages data from international crises such as the Iraq War, Arab Spring, and ongoing conflicts in Sub-Saharan Africa, offering a comprehensive view of the roles of international transfers in crisis contexts.

It is notable that used VAR model explicitly considers the variables' cointegration structures. Also, forecast error variance decompositions or impulse responses are typically used to examine the dynamic interactions between these variables. In other research papers, perfect/imperfect substitutes relationships were detected between our used variables. However, in our study, the observed relationship is complementary.

Keywords: Foreign aid, Remittances, Private transfers, Gross Domestic Product, Governance indicators, Corruption.

2.2. Introduction Chapter 2

The international community actively and significantly contributes to helping many developing nations to overcome the effects of various crises, such as political, economic, or environmental catastrophes. During crises, the international community mobilises its resources to support the affected countries. International agencies like the World Bank, International Monetary Fund (IMF), and United Nations (UN) may be major sources of these money flows. These transfers may be categorised as foreign aid, which is the topic of this paper.

Foreign aid has always been a topic of discussion in the literature. Interest in this topic has grown in the last decades, when numerous significant economic and political crises as well as humanitarian catastrophes have struck the globe.

In addition to official financial inflows, impacted nations may get personal or remittance payments from diaspora residents who maintain close ties with their families back home. The financial transfers take different types and forms, depending on the economic, social, and political situations in the beneficiaries' countries.

In this study, we analyse the impact of and correlation between these factors. We also try to demonstrate the causality that drives us to present the results of our analyses related to the Middle East and North Africa (MENA) region and Sub-Saharan Africa (SSA).

Most international transfers, and mainly those that are related to public aid, are managed by international organisations such as the World Bank and the IMF. Kanbur (2006) stated, 'Increasingly, international financial institutions, the World Bank and particularly the IMF, were held to be responsible directly or indirectly as conduits of the policies of the rich countries' (p. 1568). Therefore, the main sources of information are presented by these financial institutions, in addition to the Organisation for Economic Cooperation and Development (OECD), when the studies are related to the members' countries. Many indicators and factors in the recipient countries, such as corruption, GDP, and political stability, can play an important role in the effectiveness of these transfers and implemented projects.

According to Thorbecke (2000), the 1990s saw a significant and persistent incidence of aid fatigue, which was fuelled by growing concerns that aid dependency relationships in developing nations were being created by foreign help. There was also heated discussion about the usefulness of conditional aid. Mallaye and Yogo (2011) used cross-country panel data from 33 fragile states in Africa to analyse the relationships between the three types of transfers.

They showed that foreign aid is a complement for remittances and foreign direct investment. They found that this relationship could be affected by the level of GDP.

In this study, we aim to contribute to the existing literature by checking whether public foreign aid, remittances, GDP, and corruption are independent or interdependent in beneficiary countries. Let us briefly recall some landmark political crises that have impacted the MENA and SSA regions during the studied period. The MENA region was affected notably by the Iraq war (2003–2011), the Arab Spring (2010–2012), Syrian civil war (since 2011), and significant instability in Libya (since 2011). The main crises that impacted the SSA region were the civil war in Sudan (2003–2011), Civil war in Côte d'Ivoire (2002–2007), Islamic insurgency in Nigeria (since 2009), and Islamic insurgency and armed rebellion in Mali (since 2012).

2.2.1. Foreign Aid vs. Governance Indicators

Several studies have analysed the relationship between foreign aid and corruption. Many interesting findings in the existing literature may seem contradictory. On the one hand, Asongu (2012) investigated a panel data of 53 African countries from 1996 to 2010. He claimed that his analyses showed a positive correlation between aid and corruption. In addition, Knack (2001), based on his cross-country analyses, indicated that larger aid levels degraded the quality of governance, as measured by bureaucratic quality, corruption, and the rule of law indexes. Guilmoto and Sandron (2003) showed that financial transfers contribute to improving the health status of the population and, ultimately, to improving the quality of the workforce.

On the other hand, Okada and Samreth (2012) collected data for 120 developing countries from 1995 to 2009. They argued that foreign aid reduced corruption. In our study, we find that foreign aid and remittances jointly reduce corruption and contribute to an increase in GDP.

Asongu and Jellal (2013) examined panel data from 53 countries between 1996 and 2010 and concluded that sending help in the form of tax effort and private investment resulted in less corruption. This is consistent with our findings in the present study.

Nonetheless, they contended that corruption is increased by foreign help that is channelled through government spending.

Charron (2011) found that from 1997 to 2006, multilateral aid was robustly and positively correlated with reduced levels of corruption. He used data from 139 countries between 1984 and 2006. Kangoye (2011) performed an empirical study of 67 developing countries from 1984 to 2004, and he argued that aid dependency is generally linked to lower levels of corruption. Our results show that foreign aid and remittances could jointly lead to lower corruption and higher growth.

Alesina and Dollar (2000) investigated the relationship between assistance recipients' democracies and their levels of development. They stressed that, in addition to differences between highly democratic and less democratic countries, there are differences in the relationships between aid to colonial and non-colonial countries. They demonstrated that democratic non-colonies received almost US$14 per capita, but non-democratic former colonies earned nearly US$25. Additionally, they demonstrated that the rule of law is inconsequential when it comes to foreign aid but important when it comes to foreign direct investment.

2.2.2. Remittances and Growth

To examine the connection between remittance flows and economic growth in Turkey, Tansel and Yasar (2010) developed a dynamic macro-econometric model with Keynesian inspiration. Their results indicated that remittances had a favourable effect on growth. Our research also supports the finding that remittances boost growth in our sample of countries. Using a panel dataset for 113 developing countries, Chami et al. (2003) argued that the high flow of remittances created a dependency among recipients, which in turn induced them to reduce their labour market participation. Singh et al. (2011) argued that remittances have a negative effect on local growth in SSA. Baldé (2011) discussed the macroeconomic impact of remittances and argued that financial transfers contribute to economic development in many ways by increasing household income, which is almost entirely devoted to consumption.

Ebeke and le Goff (2010) found a positive and significant impact of remittances in countries of origin that had well-adapted, reliable tax policies. Using panel data from 36 countries in Africa from 1980 to 2009, Nyamongo et al. (2012) found that remittances are a source of economic growth. These results are compatible with our findings in the regions we studied.

Gupta et al. (2007) used panel data on 109 countries from 1984 to 2004 and argued that a 1% increase in migrant remittances helped to reduce infant and child mortality by 0.12%. These transfers help recipient countries to improve their sanitary conditions, ensuring access to healthier and more abundant food as well as to better-quality health services. Docquier and Rapoport (2006) argued that remittances may have a short-term macroeconomic impact through their effects on price or exchange rate levels. In our study, we noticed that remittances could positively affect GDP in the short term. However, Docquier and Rapoport mentioned that the long-term implications of remittances are more significant. Migrant remittances could have a positive effect on sanitary conditions, which could lead the population to be more involved in the workforce in the local community and thus positively impact growth, as indicated by our results. Knack (2001) pointed out that several studies concluded that institutional and policy gaps determine how aid affects economic growth and infant mortality. According to Knack, the institutional gap's magnitude grows as aid levels grow.

Docquier and Rapoport (2006) considered that migration is now recognised as an informal familial arrangement, with benefits in the realms of risk diversification, consumption smoothing, and intergenerational financing of investments – and that remittances are a central element of such implicit contracts. For example, when a family sends its oldest son to study overseas, it implicitly agrees that the son will be responsible for the education of the next sibling once he graduates and enters the job market. After that, both siblings will support their families during their retirement. This may also be an attempt to express gratitude for their families' efforts on their behalf, in that their parents paid their expenses when they were in need.

2.3. Data and Model Description

To address the posed questions, we constructed a panel data from 32 countries across Sub-Saharan Africa and the Middle East region, covering the period between 2002 and 2017. We collected this data set from the World Bank Data Bank, incorporating additional variables from the IMF, the UN and the OECD. Our variables include personal remittances, GDP, net official development assistance received, control of corruption. In our database, we tried to harmonize our data to obtain clearer results. As a first step, we normalized the data by using logarithmic values of foreign direct investment, foreign aid and remittances. Afterwards, we analysed the governance indicators using standardised values to ensure an accurate analysis. Furthermore, it seemed that our model might be suffering from causality issues, so we used the vector autoregressive (VAR) model, more specifically the panel VAR model, which is well-suited to our dataset given the repeated time values.

The panel VAR model seems particularly well suited to address issues that are currently at the centre of discussion in academia and in the policy arena, since it can (a) capture both static and dynamic interdependencies, (b) treat the links across units in an unrestricted fashion, (c) easily incorporate time variation in the coefficients and in the variance of the shocks and (d) account for cross-sectional dynamic heterogeneities. The panel VAR model was run with the generalised method of moments, which exploits all the orthogonality conditions between the dependent lagged variables and the error term.

We used econometric analysis to investigate the following three hypotheses relating to the relationships among our three variables of interest, namely foreign aid, GDP and remittances.

Hypothesis 1: Foreign aid granger-causes corruption

Hypothesis 2: GDP granger-causes foreign aid

Hypothesis 3: Remittances granger-causes GDP

Hypothesis 4: Foreign aid, remittances, GDP and corruption constitute a dynamic correlation/causality

The preliminary results of our panel VAR model showed that our variables could be correlated, as well as the possibility that they may correlate with their own lagged values. To resolve this issue, we used the Granger causality test to try to detect, understand and define the causality issues better. In addition, we checked the optimal lag in our model by presenting lags over several years. By using the panel VAR model and the Granger causality test, we showed that a lag of only 1 year is the optimal choice in several regressions.

The bivariate Granger Causality test is implemented by regressing the respective index on *m*-lag values of the index and *m*-lag values of the reference index.

$$Y_t = \sum Y_{t-i} + \sum X_{t-i}$$

$$X_t = \sum X_{t-i} + \sum Y_{t-i}$$

$$Y_{i,t} = \alpha_{0,i} + \alpha_{1,1} Y_{i,t-1} + \cdots + \alpha_{1,i} Y_{1,t-1} + \beta_{1,i} X_{i,t-1} + \cdots + \beta_{1,i} X_{1,-1} + \cdots + \varepsilon_{i,t},$$

$$X_{i,t} = \alpha_{0,i} + \alpha_{1,1} X_{i,t-1} + \cdots + \alpha_{1,i} X_{1,t-1} + \beta_{1,i} Y_{i,t-1} + \cdots + \beta_{1,i} Y_{1,-1} + \cdots + \varepsilon_{i,t},$$

The null hypothesis that the reference index does not Granger-cause the chosen index was accepted if and only if no lagged values of reference were retained in the regression. An F-test was then used to determine whether the coefficients of m-lag values of the reference index were jointly equal to zero. The p-values for each F-test were reported in table format.

$$Rem_t = \alpha_0 + \alpha_1 Rem_{t-1} + \cdots + \alpha_{1,2} Rem_{t-n} + \alpha_2 Aid_{t-1} + \cdots + \alpha_{2,1} Aid_{t-n} + \alpha_3 GDP_{t-1} + \cdots + \alpha_{3,1} GDP_{t-n} + \gamma_4 C_t$$

$$Aid_t = \beta_0 + \beta_1 Aid_{t-1} + \cdots + \beta_{1,2} Aid_{t-n} + \beta_2 Rem_{t-1} + \cdots + \beta_{2,1} Rem_{t-n} + \beta_3 GDP_{t-1} + \cdots + \beta_{3,1} GDP_{t-n} + \gamma_4 C_t$$

$$GDP_t = \gamma_0 + \gamma_1 GDP_{t-1} + \cdots + \gamma_{1,2} GDP_{t-n} + \gamma_2 Aid_{t-1} + \cdots + \gamma_{2,1} Aid_{t-n} + \gamma_3 logRem_{t-1} + \cdots + \gamma_{3,1} GDP_{t-n} + \gamma_4 C_t$$

where Rem is remittances, Aid is foreign aid, GDP is the log of real GDP, C is the exogenous control variable, $\alpha_1 \ldots 4$, $\beta_1 \ldots 4$ and $\gamma_1 \ldots 4$ are coefficients, and α_0, β_0 and γ_0 are constants.

In addition, we know that using a lagged value of the variables is important to see the causality issues more clearly. That is why we searched to find the optimal lag value for our model. Our results showed that the optimal lag for our model is 1 year with the smallest MBIC, MAIC and MQIC, as it minimises the p-value of Hansen's J. We used

Andrew and Lu's (2001) selection criterion for this model. Many other results are significant when we use lags of 2 and 3 years. It is notable that the short-term dynamics and long-term relationships are now frequently kept apart in this paradigm. Because they can be linked to relationships drawn from economic theory, cointegration or long-term interactions are frequently of particular interest (Lütkepohl 2005).

2.4. Results

To check the relationships between our variables, we ran several regressions using our Panel VAR model on the totality of our sample. We used the Granger causality test to check which variable was causing changes in the other variables. We based our analyses on two hypotheses:

- *Panel VAR–Granger causality Wald test*
  - *If H_0 is verified, the excluded variable does not Granger-cause the equation variable*.
  - *If H_a is verified, the excluded variable Granger-causes the equation variable*.

<u>SSA and MENA regions:</u>

We studied the relationship between foreign aid and GDP. We noticed that these two variables are highly correlated. By using the Granger causality test, we could show that increases in GDP could Granger-cause increases in foreign aid.

If the recipient country demonstrates an increasing GDP and an effective governance, this could encourage the international community to provide help and to implement projects through donors and aid agencies by expecting better income returns.

A higher GDP may also indicate a more stable economy, which can improve the efficiency of aid. Growth-oriented economies tend to use aid for development initiatives like infrastructure, healthcare, and education, which further support sustainable growth, rather than for crisis management.

Hence, we propose that effective implementation of foreign aid projects may enhance the state of infrastructure while simultaneously enacting other laws and regulations.

MENA Region:

In the MENA region, our empirical analyses showed that growth coupled with an enhancement of the corruption index, which means decreasing corruption, could attract foreign aid as well as remittances. This, in turn, could have favorable reinforcing effects by further increasing growth and decreasing corruption. Growth accompanied by decreasing corruption, which means implementing and improving policy implementation, attracts international public transfers (development aid) and family transfers (remittances).

In turn, corruption declines and growth is favourably impacted. This dynamic virtuous circle implies a form of complementarity between aid and remittances. Complementarity implies that the two types of transfers tend to evolve in the same direction, either upwards or downwards. Conversely, substitutability implies that one increases when the other decreases: for example, if public aid falls for a given reason, remittances would increase to compensate, in the spirit of the property of perfect substitutability of Barro and Becker (1974). Also, Mercier-Ythier (2006) discussed an imperfect substitutability of transfers in his theory model. He argued that most remaining private payments are thought to be complementary to the public redistributive transfers.

Consequently, in the MENA region, our results showed a dynamic complementarity because they are closely linked to the development process. We can also highlight that a constructive interaction between aid flows and policies is an important factor for development. The Barro–Becker property of perfect substitutability is a microeconomic–static-type mechanism, implying a *ceteris paribus* clause: i.e. if, for some exogenous reason, public aid varies upwards or downwards, a variation in public aid leads to a variation in private aid of the same amount in the opposite direction. This cancels out the consequences of the variation in public aid on the allocation of resources and therefore e.g. on growth.

Table 2.2 shows that remittances can attract foreign aid in the Middle East. Since the remittances are linked directly to households, the families can contribute to attracting foreign aid. Households use remittances to respond to their daily consumption needs as well as, less frequently, to realise investments. These projects could increase the GDP of the given country in the long term.

Furthermore, when foreign aid is used effectively in developing nations to execute beneficial initiatives, the remittances paid by migrants to their families can be invested in successful businesses, which can lead to more robust economic activities. For instance, the beneficiaries of these transfers might find themselves paying only one electricity bill instead of two (that is, one for the government and one for private electric generator companies to make up for the hours when the state does not provide electricity). This example might also apply to paying hefty private transport expenses, which can be up to five times more expensive than using public transport. Along with numerous other benefits, these lower costs may enable families to invest the proceeds of transfers, perhaps increasing their incomes in the process. As our econometric results indicate, remittances may therefore contribute to an increase in GDP.

In any event, favourable internet services, fast start-up times, and up-to-date legal frameworks can encourage foreign initiatives to be carried out in the recipient nation. Remittances and foreign direct investment will consequently rise dramatically, which will also favourably affect economic growth.

Figure 2.1

Causal Interactions: Middle East Countries

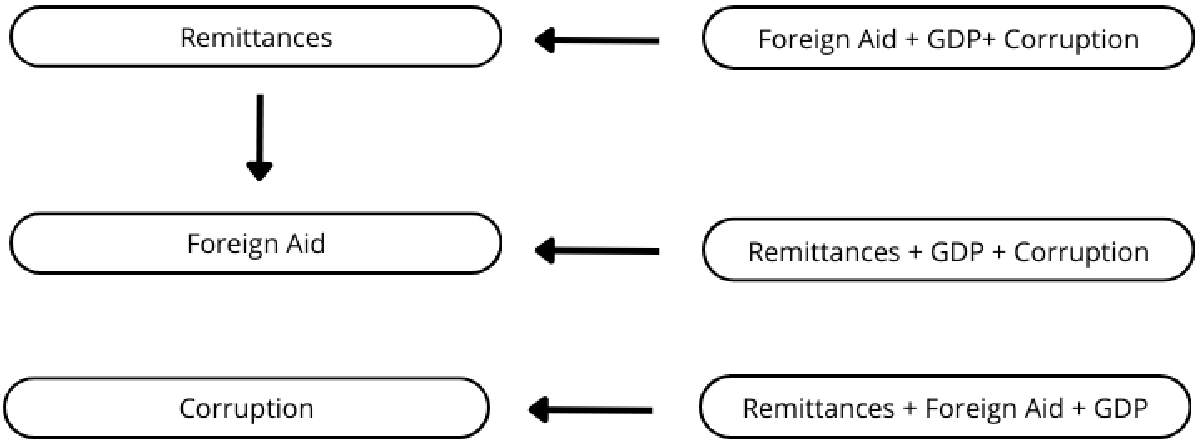

Figure 2.2

Causal Interactions: Sub- Saharan Africa and the Whole Panel

2.5. Conclusion

Our findings reveal a robust relationship between foreign aid, remittances, economic growth, and anti-corruption efforts, particularly in the MENA and Sub-Saharan Africa regions. We observed that increases in GDP tend to attract further foreign aid, suggesting a proactive international response to positive economic indicators. Moreover, our results in the MENA region, confirm a significant complementarity between development aid and remittances: both tend to rise and fall together, suggesting that they are mutually reinforcing rather than substitutable. This synergy appears essential for fostering sustainable development and reducing corruption, thereby enhancing the effectiveness of foreign aid.

Our research contributes to the existing literature by delineating the nuanced roles of various types of financial transfers in regions affected by crises, underlining the importance of strategic aid implementation and policy coherence in enhancing the developmental impact of foreign aid.

Overall, the economic analysis for these findings underscores the importance of managing remittances and foreign aid as complementary tools rather than separate channels , to promote economic development and resilience, especially in areas vulnerable to political and economic instability. This all-encompassing strategy can optimize the effects of foreign transfers in promoting long-term, sustainable growth as well as immediate alleviation.

Future studies should continue to investigate these relationships across different geopolitical contexts and consider the impacts of such dynamics on regional stability and development.

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3. Chapter 3: Informal sector, Remittances and Political Stability: A study of Granger-causality in four large geopolitical sets (co-écrit par Mamadou Lah et Hadi Salameh)

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3.1. Abstract

This paper investigates the relationships between remittances, the informal sector, and political stability across various large geopolitical sets, including the Middle East and North Africa (MENA), Sub-Saharan Africa, Latin America, and the Organisation for Economic Co-operation and Development (OECD) countries. Employing Granger causality tests to determine the predominate direction of causality and panel vector autoregressive models, we explore the dynamics of these relationships over short, medium, and long-term periods.

Our findings reveal a significant short-term impact of remittances on the growth of the informal sector in the MENA, Sub-Saharan Africa, and Latin America, suggesting that remittances directly influence economic activities within this sector, likely due to their use in undeclared activities and the funding of informal local businesses. However, the influence of remittances wanes over time, indicating their primary role in addressing immediate economic needs rather than fostering long-term sector growth. Political stability shows minimal direct causal interaction with the informal sector, hinting at the sector's role as an adaptive mechanism in politically volatile regions.

In OECD countries, remittances maintain a persistent influence on the informal sector over longer periods, reflecting their role in more strategic economic decisions. Additionally, our study explores the complex dynamics in countries with high remittance-to-GDP ratios, identifying a strong predictive power of the informal sector size on remittance flows, which points to the sector's pivotal economic role. We have extended our analysis to OECD countries, using outward remittances as a proxy for inward migration. We found that the size of the informal sector can predict outward remittance flows and political stability, highlighting the crucial role of the informal economy in migration and political dynamics.

The results underscore the need for region-specific policy interventions and highlight the importance of understanding the temporal dynamics of remittances. This study contributes to the discourse on economic development strategies, suggesting that leveraging remittances effectively requires comprehensive policy approaches that consider their varied impacts across different regional and economic contexts.

Keywords: informal sector, remittances, political stability, Granger causality, PVAR model, migration
JEL Classification: C32, F22, F24, O17

3.2. Résumé

Cet article explore les liens entre les envois de fonds, le secteur informel et la stabilité politique dans plusieurs ensembles géopolitiques majeurs, dont le Moyen-Orient et l'Afrique du Nord (MENA), l'Afrique subsaharienne, l'Amérique latine et les pays de l'Organisation de Coopération et de Développement Économiques (OCDE). En utilisant des tests de causalité de Granger pour déterminer la direction prédominante de la causalité et des modèles autorégressifs vectoriels de panel, nous examinons la dynamique de ces relations sur des périodes courtes, moyennes et longues.

Nos résultats révèlent un impact significatif à court terme des envois de fonds sur la croissance du secteur informel dans la région MENA, l'Afrique subsaharienne et l'Amérique latine, suggérant que les envois de fonds influencent directement les activités économiques au sein de ce secteur, probablement en raison de leur utilisation dans des activités non déclarées et le financement d'entreprises locales informelles. Cependant, l'influence des envois de fonds diminue avec le temps, indiquant leur rôle principal dans la réponse aux besoins économiques immédiats plutôt que dans la promotion de la croissance à long terme du secteur. La stabilité politique montre une interaction causale directe minimale avec le secteur informel, suggérant le rôle du secteur comme mécanisme d'adaptation dans les régions politiquement instables.

Dans les pays de l'OCDE, les envois de fonds maintiennent une influence persistante sur le secteur informel sur de plus longues périodes, reflétant leur rôle dans des décisions économiques plus stratégiques. De plus, notre étude explore la dynamique complexe dans les pays ayant des ratios envois de fonds/PIB élevés, identifiant un fort pouvoir prédictif de la taille du secteur informel sur les flux de transferts de fonds, ce qui souligne le rôle économique central du secteur. Nous avons étendu notre analyse aux pays de l'OCDE, en utilisant les envois de fonds sortants comme indicateur de la migration entrante. Nous avons constaté que la taille du secteur informel peut prédire les flux de fonds sortants et la stabilité politique, soulignant le rôle crucial de l'économie informelle dans la dynamique migratoire et politique.

Les résultats soulignent la nécessité d'interventions politiques spécifiques à chaque région et l'importance de comprendre la dynamique temporelle des envois de fonds. Cette étude contribue au discours sur les stratégies de développement économique, suggérant qu'une

utilisation efficace des envois de fonds nécessite des approches politiques globales qui prennent en compte leurs impacts variés selon les contextes régionaux et économiques.

Mots clés : secteur informel, envois de fonds, stabilité politique, causalité de Granger, modèle PVAR, migration
Classification JEL : C32, F22, F24, O17

3.3. Introduction Chapter 3

All economies worldwide have to deal with the more or less significant presence of the informal economy. In some regions, it may represent up to 70% of the global economy. Several factors are associated with this sector, including political stability, taxation, economic growth, and remittances. In this article, we explore the subtle link between the informal economy, political stability, and remittances through a comparative study of four large geopolitical sets: the Middle East/North Africa (MENA), Sub-Saharan Africa (SSA), the Organisation for Economic Co-operation and Development (OECD) countries and Latin America.

Most articles on the informal economy focus on the determinants of the size of the informal economy and on estimating its size (Amaral & Quintin, 2006; Dabla-Norris et al., 2008; Ihrig & Moe, 2004; Loayza, 1996; Schneider & Enste, 2000, 2010, 2017; Tanzi, 1983, 1999). Our approach is empirical and focused on the panel vector autoregressive model (PVAR) and Granger causality test.

Many papers have studied the link between political stability and remittances (Abbas et al., 2017; Aydas et al., 2005; Catrinescu et al., 2009, among others), but very few have been interested in the informal economy at the same time, and few have conducted a comparative study between MENA and SSA, Latin America and OECD regions. These regions differ in their political systems, the level of remittances as a percentage of GDP and the size of the informal sector.

Depending on the perspective, the informal economy can both weaken and support political stability. On the one hand, in times of political stability, it can stimulate the growth of the informal economy by building confidence and reducing disruption. On the other hand, during periods of political instability, it can undermine informal activity through increased repression, erosion of trust and economic uncertainty. The informal economy can also have both positive and negative effects on political stability through (a) the provision of jobs and livelihoods to a significant proportion of the population, thereby reducing poverty and strengthening political stability, and (b) tax evasion, corruption and a lack of social protection.

In many economies around the world, the informal economy is often the foundation of family support, while remittances are the link that strengthens that foundation. Indeed, remittances directly impact the informal economy by (a) providing financial support to small, informal businesses and (b) stimulating consumption and local demand, targeting both formal and informal businesses.

To determine which direction of causality prevails, we conducted a Granger causality test. In the four large geopolitical sets, examining the short-term impacts (lag 1), the results show a positive correlation between remittances and the size of the informal sector. We found that remittances Granger-cause the size of the informal sector. Political stability as a separate variable had no causal relationship with the informal sector, but remittances and political stability together Granger cause an informal sector. However, we did not find a significant result when we ran our test in the medium to long run for Latin America, SSA and MENA. Therefore, we conclude that the effect of these two variables in these regions is only short-term. This could mean remittances are invested in primary needs rather than formal or informal investments.

However, In OECD countries, medium to long-term tests yielded significant results, matching those of the short term. Nevertheless, we found that political stability Granger causes remittances on the one hand, and the informal sector and remittances Granger cause political stability both together and separately on the other hand.

Additionally, in an increasingly globalized world, the flow of remittances and migration has significant economic and social impacts, particularly within OECD countries which are characterized by complex interdependencies between developed and developing economies. This paper also explores the intricacies of outward remittances used as a proxy for inward migration, examining their relationships with the informal sector and political stability in regions like the USA/Canada and EU/UK. We found that the size of the informal sector predicts outward remittances (as a proxy for inward migration) and political stability, but remittances do not significantly influence the informal sector or political stability. More precisely, in the short-term dynamics (Lag 1), the immediate effects of remittances on the informal sector and political stability are minimal or delayed. In the medium to long-term dynamics (Lags 2 to 5), the size of the informal sector predicts outward remittances and political stability, but remittances do not significantly influence the informal sector or political stability.

Finally, to examine how dependency on remittances might affect the relationships between remittances, political stability, and the informal sector, we analyze the impact of remittances on the informal sector and political stability in countries with high remittance dependence (defined as a remittance-to-GDP ratio exceeding the OECD average of 0.84% and the median of our sample evaluated to 1.45%). We found a strong link between remittances and the informal sector. However, these economic factors do not directly translate into political changes.

Further, this paper is structured as follows: The second section briefly reviews the existing literature. The third section describes the model, methodology, data and research techniques. The fourth section analyses the empirical results, and the final section provides concluding remarks.

3.4. Literature review

Many articles have examined the link between political stability and remittances, such as Catrinescu et al. (2009), Abbas et al. (2017) and Aydas et al. (2005). These papers analyse this relationship in terms of several factors in remittance-receiving countries. We contribute to this literature by focusing on the informal economy at the same time. In addition, we examine this link through a comparative study between four large political sets (MENA, SSA, OECD and Latin America). According to the World Bank dataset, these regions and countries exhibit different levels of political stability. We used the panel vector autoregressive model (PVAR), GMM estimation and Granger causality test.

Catrinescu et al. (2009) used dynamic panel data analysis to investigate the relationship between remittances and growth, concluding that remittances were more likely to contribute to longer-term growth in countries with higher-quality political and economic policies and institutions.

Abbas et al. (2017) employed the GMM method to examine the impact of macroeconomic, financial and political factors on remittances to Pakistan using data from 1972–2012. The authors found a positive correlation between remittances and institutional quality.

Aydas et al. (2005) used ordinary least squares to examine the effect of various macroeconomic variables on remittance flows in Turkey for the period 1965–1993. They found a positive and significant effect on growth, indicating the importance of sound exchange rate policies and economic and political stability in attracting remittance flows.

These results are consistent with our findings, but only for the OECD countries. In these countries, we conclude that political stability Granger causes remittances in the short run. We do not find a causal relationship for the SSA-MENA region and the Latin America region for the same run. However, the informal sector and political stability jointly Granger cause remittances for the Latin America region on short run.

Elbahnasawi and Ellis (2016) studied the informal sector and political instability. They found that political instability, social polarisation along ethnic and religious lines, and autocratic patterns of authority were associated with larger informal economies.

By regressing the size of the informal economy on six indicators of world governance and across 149 countries over six years, Friedman (2014) found that in a country where citizens perceive the current government as unstable, think the quality of regulations is poor, and feel that corruption is not being tackled, there is a correlation with a larger informal economy. The stability of a political system may be a prerequisite for the growth of a formal economy. Entrepreneurs need to be confident that business regulations are reasonably stable and that contracts signed now will be valid in the future to transition from the informal to the formal economy. Countries must develop regulations that motivate individuals to move into the formal economy. Policies encouraging private sector growth, such as access to capital, favourable interest rates and the lure of foreign investment, are examples of such initiatives. The results of our paper are consistent with these considerations, showing that political stability as a separate variable does not Granger cause the informal sector in our studied four geopolitical sets. However, for the OECD countries, we found that the informal sector does Granger cause political stability in medium-long run.

Chatterjee and Turnovsky (2018) analysed the impact of remittances on the informal sector by developing a general equilibrium framework to better understand the dynamic absorption of remittances in a two-sector, small, open economy. The researchers determined that the impact of remittances depends critically on how they affect the recipient economy.

Njangang et al. (2018) analysed this link for 30 SSA countries over the period 1991–2015 and showed that remittances significantly increase the size of the informal economy. They used OLS and GMM as empirical strategies. These results are in line with our findings. We found that remittances Granger-cause the informal sector in MENA, SSA and Latin America in short run. We also found that remittances and political stability jointly

Granger-cause the informal sector in these regions in short run. In the OECD countries, the same outcomes are seen in the short, medium and long runs.

3.5. Data[1] and methodology

3.5.1. Informal sector

The informal sector is an unobservable phenomenon. Therefore, estimation methods are needed. Although this estimation can be a challenging task due to the clandestine nature of the informal economy, economists and researchers have developed several methods and indicators that can provide rough estimates of the shadow economy.
Here are some commonly used approaches:

- National accounts discrepancy method: This method compares the reported national income, as measured by official statistics, with the total expenditure in the economy. The discrepancy between these two figures can be attributed to unreported or underreported economic activities that are part of the shadow economy. By analysing this gap, researchers can estimate the size of the shadow economy relative to the official economy.
- Currency demand method: The currency demand method focuses on estimating the amount of cash in circulation used for transactions in the shadow economy. Researchers examine the velocity of money (how often it changes hands) and the ratio of currency to GDP. Analysts can infer the size of the shadow economy by comparing the observed amount of cash in circulation with the expected amount based on legitimate transactions.
- Labour market indicators: The shadow economy often involves unreported employment and undeclared wages. Researchers analyse labour market indicators, such as the difference between official and actual employment figures, the number of workers without social security coverage, and discrepancies in tax declarations. These

[1] The philosophy of database construction is provided in Appendix 2.

indicators can provide insights into the extent of informal employment and economic activity.

- Indirect approaches: Several indirect methods are used to estimate the shadow economy. These include analysing electricity consumption patterns, analysing discrepancies in trade data, studying the sales of certain commodities (e.g. tobacco or alcohol) often associated with underground activities, and conducting surveys or interviews to capture individuals' self-reported participation in the shadow economy.
- Multiple indicators: Estimating the shadow economy is complex, and no single method can provide a definitive measurement. Researchers often use a combination of the above approaches and indicators to obtain a more comprehensive estimate. By triangulating different data sources and methodologies, they can minimise bias and arrive at a reasonable approximation.

This paper uses the method of multiple indicators and causes (MIMIC) referred to Medina and Schneider (2017). This method is among the best known and widely used in the literature.

MIMIC

The MIMIC approach is to estimate the size of the informal economy. Unlike other methods that rely on a single indicator, the MIMIC model considers the multiple causes and effects of the informal economy. This method exploits the interactions between the observable causes and effects of the informal economy itself. Formally, the MIMIC model consists of two components: the structural model and the measurement model. The structural model describes how a set of exogenous causal variables influence the latent variable (in this case, the size of the informal economy).

Model: Mathematically, the structural model can be expressed as follows:

$$I = \beta X + \varepsilon$$

Where:

I represents the latent variable (the size of the informal economy).

X stands for the exogenous causal variables.

β represents the coefficients or weights determining the relationship between the causal variables (X) and the latent variable (I).

ε stands for the error term or the unobserved factors affecting the latent variable.

The equation states that the size of the informal economy (I) is determined linearly by the exogenous causal variables (X) with coefficients β. The error term (ε) captures any unobserved or unaccounted-for factors that affect the size of the informal economy but are not directly accounted for by the exogenous variables.

In the MIMIC model, the exogenous causal variables (X) may include factors such as income inequality, unemployment rates, tax burden, regulatory burden, institutional quality, size of the agricultural sector, self-employment and other relevant indicators associated with the informal economy.

The structural model provides the basis for understanding how the causal variables influence the latent variable (the size of the informal economy), but it does not directly measure the latent variable itself. This is where the measurement model comes in.

The measurement model in the MIMIC approach links the latent variable (the size of the informal economy) to a set of selected indicators. It determines how these observable indicators relate to the unobserved informal economy.

Mathematically, the measurement model can be expressed as follows:

$Y = \gamma I + \mu$

Where:

Y represents the observed indicators (e.g. electricity consumption, money demand, labour force participation, real GDP, etc.).

γ is the factor loadings or weights that determine the relationship between the latent variable (I) and the observed indicators (Y).

I represents the latent variable (the size of the informal economy).

μ stands for the measurement error or unobserved factors that affect the observed indicators but are not directly accounted for by the latent variable.

The equation states that the observed indicators (Y) are linearly related to the latent variable (I) with factor loadings γ. The measurement error term (μ) captures any unobserved or unaccounted-for factors that affect the observed indicators but are not directly attributable to the latent variable.

Within the context of the MIMIC model for estimating the size of the informal economy, the observed indicators (Y) can be selected on the basis of their relevance and association with the informal economy. These indicators should capture different manifestations or symptoms of the informal economy, such as electricity consumption, money demand and other relevant variables.

3.5.2. Panel Vector Autoregression (PVAR) and Granger causality test

We also used the PVAR model and the Granger causality test. To answer the above questions, we created three panels' data from 1996 to 2017 for the following geopolitical sets: The MENA and SSA (25 countries), Latin America (22 countries) and OECD countries (38 countries). We collected our data from the World Bank's database (Databank).

Our variables used are personal remittances, GDP and political stability, in addition to the informal sector. In our database, we tried to harmonise our data to obtain clearer results. As a first step, we normalized the data by using logarithmic values of remittances and the informal economy. Furthermore, it seemed that our model might suffer from causality problems, so we used the vector autoregressive (VAR) model, more specifically, the PVAR model, which is well-suited to our dataset given the repeated time values. The PVAR model seems to be particularly well suited to address issues that are currently at the centre of academic and policy discussion, as it can (a) capture both static and dynamic interdependencies, (b) treat the links between units in an unrestricted manner, (c) easily incorporate time variation in the coefficients and in the variance of the shocks, and (d) account for cross-sectional dynamic heterogeneities.

The PVAR model was run using the generalised method of moments, which exploits all the orthogonality conditions between the dependent lagged variables and the error term.

Hypothesis 1: The informal sector and remittances vary in the same direction.

Hypothesis 2: Political stability and remittances vary in the same direction.

Hypothesis 3: Remittances and political stability are dynamically correlated with the informal sector.

The preliminary results of our PVAR model showed that our variables might be correlated with each other, as well as the possibility that they might be correlated with their own lagged values.

To address this issue, we used the Granger causality test to better identify, understand and define the causality issues. Introduced by Clive Granger in the 1960s, this method focuses on improving forecasts, aligning perfectly with our primary objective: to evaluate whether the information contained in one time series (e.g., remittances) can better predict the evolution of another series (e.g., the size of the informal sector). Granger developed these causality models in response to criticisms of the structural equations in macroeconomics, where the pure exogeneity or endogeneity of variables was often inadequately ensured.

Granger causality presents several advantages that justify our choice. Firstly, it is conceptually simpler and easier to interpret than other approaches, such as the Sims causality proposed in the 1970s. The Sims method, based on impulse response analysis, is more complex and requires stronger assumptions about the model structure, which can be difficult to justify in our context where relationships between variables are complex and potentially nonlinear.

Secondly, Granger causality requires fewer data and a priori assumptions, making it more suitable for situations where data are limited or incomplete, as is often the case in developing countries where the informal sector is predominant. Finally, it has been widely used and accepted in econometric literature since its introduction, facilitating the comparison of our results with those of previous studies and enhancing the validity of our conclusions.

Although Granger causality has certain limitations, particularly in terms of strict causal interpretation (since it does not establish causality in the strict sense, but rather temporal precedence), it remains a valuable tool for analyzing temporal relationships between economic and financial variables. In the context of our study, its historical and practical advantages, as well as its ability to capture dynamic relationships between variables, outweigh its drawbacks, justifying our methodological choice.

The bivariate Granger causality test in two variables is carried out by predicting a specific index using its own past values (m-lag) and the past values (m-lag) of another reference index.

$$Y_t = \sum Y_{t-i} + \sum X_{t-i}$$

$$X_t = \sum X_{t-i} + \sum Y_{t-i}$$

$$Y_{i,t} = \alpha_{0,i} + \alpha_{1,1} Y_{i,t-1} + \cdots + \alpha_{1,i} Y_{1,t-1} + \beta_{1,i} X_{i,t-1} + \cdots + \beta_{1,i} X_{1,-1} + \cdots + \varepsilon_{i,t},$$

$$X_{i,t} = \alpha_{0,i} + \alpha_{1,1} X_{i,t-1} + \cdots + \alpha_{1,i} X_{1,t-1} + \beta_{1,i} Y_{i,t-1} + \cdots + \beta_{1,i} Y_{1,-1} + \cdots + \varepsilon_{i,t},$$

The null hypothesis, which states that the reference index does not influence the selected index according to Granger causality, is accepted if none of the lagged values of the reference index are included in the regression. An F-test was then performed to check whether all coefficients of the m-lagged values of the reference index were simultaneously zero. The p-values for each F-test are presented in a table.

$$Informal\,S_t = \alpha_0 + \alpha_1 Informal\,S_{t-1} + \cdots + \alpha_{1,2} Informal\,S_{t-n} + \alpha_2 PS_{t-1} + \cdots + \alpha_{2,1} PS_{t-n} + \alpha_3 Rem_{t-1} + \alpha_{3,1} Rem_{t-n} + \gamma_4 C_t$$

$$Rem_t = \alpha_0 + \alpha_1 Rem\,S_{t-1} + \cdots + \alpha_{1,2} Rem\,S_{t-n} + \alpha_2 PS_{t-1} + \cdots + \alpha_{2,1} PS_{t-n} + \alpha_3 Informal\,S_{t-1} + \alpha_{3,1} Informal\,S_{t-n} + \gamma_4 C_t$$

$$PS_t = \alpha_0 + \alpha_1 PS_{t-1} + \cdots + \alpha_{1,2} PS_{t-n} + \alpha_2 Informal\,S_{t-1} + \cdots + \alpha_{2,1} Informal\,S_{t-n} + \alpha_3 Rem_{t-1} + \alpha_{3,1} Rem_{t-n} + \gamma_4 C_t$$

Where *Informal S* stands for the informal sector, *Rem* represents remittances, *PS* stands for political stability, and C is the exogenous control variable; α_1..4, β_1..4, γ_1..4 are the coefficients, α_0, β_0, γ_0 are the constants.

To give more consistency to our work, we also conducted collinearity tests and stationarity tests. These tests are crucial for ensuring the reliability of our time series data. Collinearity tests are necessary to detect multicollinearity issues that could distort our regression estimates and undermine the validity of the causal relationships. Stationarity tests confirm that the statistical properties of the series do not change over time, which is a key assumption for Granger causality analysis. Details and analysis of these tests can be found in Appendix 4 and 5.

Additionally, we conducted impulse response function (IRF) and forecast error variance decomposition (FEVD) analyses, with a detailed analysis provided in the appendix. The coherence between Granger causality, IRF, and FEVD results enhances the robustness of the findings. The detailed analyses of IRF and FEVD can be found in Appendix 6 and 7.

Moreover, it is important to use a lagged value for the different variables to see causality issues more clearly. Therefore, we searched for the optimal lag value for our model. Our results show that the optimal lag for our model is the lag of one year with the smallest MBIC, MAIC and MQIC, as it minimises Hansen's J (p-value) for SSA and MENA and Latin America geopolitical sets, while the optimal lag is lag 2 for OCDE set[2]. We refer here to Andrews and Lu's (2001) selection criteria. Many other results are significant when we use lag 2 and lag 3. We will delve deeper into these findings in the following sections.

[2] Economic and statistical considerations lead us to choose the optimal lag. The details of this choice are provided in Appendix 3.

3.6. Results:

In the present study, we observe a significant correlation between the variables that form its core subject. As mentioned at the outset, we have analysed the correlation and causality between the indicators and variables used.

3.6.1. MENA and Sub-Saharan Africa

3.6.1.1. Short-term impact

In the short term, there is a notable positive correlation between remittances and the size of the informal sector within MENA and Sub-Saharan Africa. It appears that remittances Granger-cause growth in the informal sector, likely because these funds are often channelled into undeclared activities, as indicated in Table 3.1 and Figure 3.1. This trend suggests that an increase in remittances could expand the informal sector, possibly due to the funding of informal businesses or increased demand for informal goods and services. Separately, political stability does not exhibit a direct causal link with the informal sector, which may reflect the region's adaptation to enduring political instability.
Furthermore, the combined influence of remittances and political stability on the informal sector size indicates a complex interaction, suggesting that both elements contribute to shaping the informal sector dynamics in the short term.

3.6.1.2. Medium-term and long-term dynamics

Expanding the analysis to include medium-term effects (lag 2), remittances continue to Granger-cause the informal sector size. However, the joint impact of remittances and political stability on the informal sector becomes statistically insignificant with an extended lag. This diminishing influence after two periods suggests that remittances and political stability have a more pronounced short-term effect, potentially indicating that remittances in the medium term primarily address basic needs rather than fostering investments in formal or informal businesses.

3.6.1.3. Implications

The findings from this analysis predominantly pertain to the unique context of MENA and Sub-Saharan Africa and should be interpreted with regional specifics in mind.

- Remittances and the informal sector in MENA and Sub-Saharan Africa

Firstly, the robust positive correlation between remittances and informal sector size in the short term suggests that remittances significantly bolster the informal sector in these regions. This support may stem from factors like limited access to formal financial services and heightened demand for informal goods and services, which promotes the sector's growth. Additionally, in the short term, remittances are typically used to meet basic needs, thus further driving demand for informal sector services.

Secondly, the lack of a causal link beyond two periods might explain why remittance flows are predominantly spent in undeclared activities. This indicates a short-lived effect where remittances are used for immediate needs, with minimal long-term investment in formalizing or expanding informal businesses.

However, other factors potentially influencing undeclared remittance spending include limited access to formal services, high formalization costs, and bureaucratic inefficiencies.

- Political stability and the informal sector

The absence of a direct causal relationship between political stability and the informal sector in the short term may be due to the regional adaptation to political instability, where the informal sector serves as a coping mechanism during fluctuating political conditions.

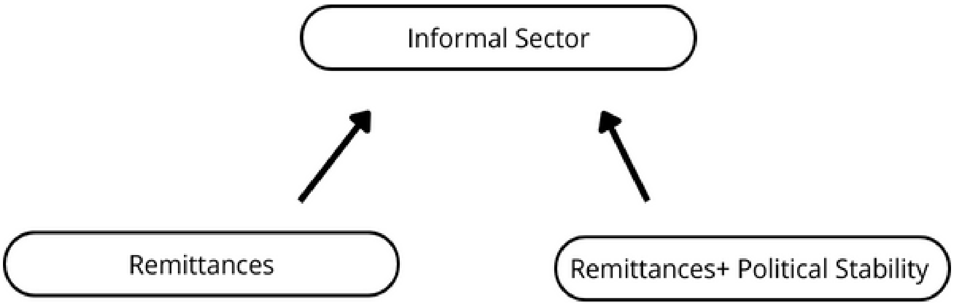
- Medium-term and long-term dynamics

In the medium to long term, the influence of remittances and political stability on the informal sector wanes, potentially due to diversification of investments into more formal sectors and improvements in institutional frameworks that encourage formalization.

Understanding the intricate dynamics between remittances, the informal sector size, and political stability in MENA and Sub-Saharan Africa is essential for policymakers and development practitioners aiming to foster sustainable economic growth and inclusive development in these regions.

Figure 3.1

Causal interactions: Informal sector, remittances and political stability in MENA and Sub-Saharan Africa (lag 1).



3.6.2. Latin America

3.6.2.1. Short-term analysis of remittances and the informal sector

Our analysis of the Latin America region reveals a clear positive correlation between remittances and the size of the informal sector. This correlation suggests that increases in remittances lead to a corresponding increase in the informal sector. The data indicates that remittances not only Granger-cause the informal sector, suggesting a predictive relationship from past remittance values to future informal sector size, but also show reverse causality. This reverse causality means that changes in the informal sector size can predict future remittance values, highlighting a complex, bidirectional relationship between these variables.

Moreover, while political stability alone does not show a causal relationship with the informal sector, it appears jointly with the informal sector to Granger cause remittances, as demonstrated in Table 3.4 and Figure 3.2.

3.6.2.2. Causal relationships beyond a one-period lag

The analysis suggests no significant causal links among remittances, the informal sector, and political stability beyond a one-period lag. This observation points to the predominance of short-term interactions between these variables, with minimal long-term influences detectable with the current data and modelling approach.

3.6.2.3. Implications for policy and research

Given the predominantly short-term causal relationships identified, policymakers and development agencies might need to focus on immediate interventions that address the impacts of remittances and the informal sector. It is crucial to continue research to unearth the long-term drivers influencing these variables in Latin America, which might include factors like global economic trends, technological advances, and changes in migration patterns.

3.6.2.4. Recommendations for further research and policy formulation

- Model and data enhancements: Employ alternative model specifications and expand lag structures to verify the robustness of these findings. Including more comprehensive variables could provide a deeper understanding of long-term influences.
- Qualitative insights: Augment quantitative analyses with qualitative research to explore the mechanisms underlying these relationships more thoroughly.
- Regional and contextual considerations: Recognize the potential for significant regional variations within Latin America, which could impact the generalizability of findings and necessitate tailored policy responses.

3.6.2.5. Understanding reverse causality

The observed reverse causality between the informal sector size and remittances is intriguing but must be interpreted with caution due to the limitations inherent in Granger causality tests, such as the potential for omitted variable bias. This might imply other underlying factors, such as economic conditions, that simultaneously affect both the informal sector and remittance flows.

3.6.2.6. Exploratory recommendations

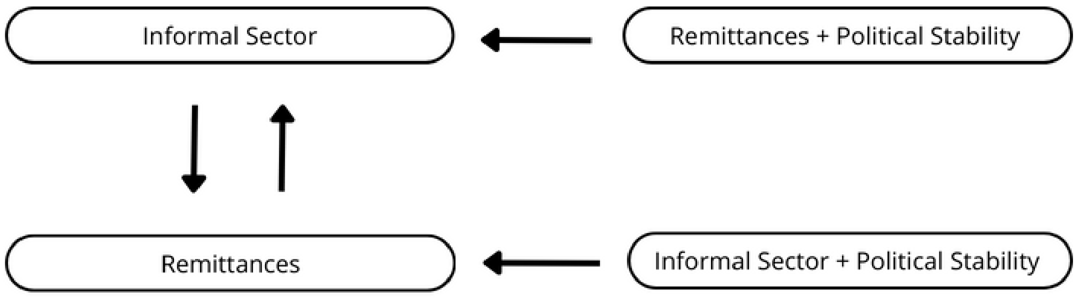
- Theoretical development: Craft a theoretical framework to explain potential mechanisms by which a larger informal sector could lead to increased remittances.

- Control for confounders: Integrate additional controls in the analytical models to address potential confounding variables that could influence both the informal sector and remittances.

The findings underscore the dynamic and interwoven relationship between remittances and the informal sector in Latin America, necessitating nuanced analyses and targeted policy interventions to harness these interactions for regional economic development. Further investigations are needed to fully understand the complexities of these relationships and to design effective development strategies tailored to the unique contexts of Latin American countries.

Figure 3.2

Causal interactions: Informal sector, remittances and political stability in Latin America (lag 1)



3.6.3. Analysis of remittances, informal sector, and political stability in OECD countries

This section systematically examines the relationship between remittances, the informal sector, and political stability within the context of Organisation for Economic Co-operation and Development (OECD) countries. Utilizing Granger causality tests over multiple time frames—short, medium, and long-term—this analysis reveals consistent positive correlations and dynamic interplays that suggest nuanced policy implications.

The role of remittances in economic development has been extensively studied, yet its impact within developed economies, particularly in relation to the informal sector and political stability, requires deeper investigation. OECD countries, characterized by higher

levels of economic development and political stability, offer a unique setting to explore these dynamics.
Granger causality tests were applied to a longitudinal data set to explore the relationships between remittances received, the informal sector, and political stability across different lags. The analysis was segmented into short-term (1 year), medium-term (2-3 years), and long-term (5 years) effects to distinguish immediate from delayed impacts.

3.6.3.1. Short-term and medium-term findings

- Remittances and informal sector: There is a consistent positive correlation where remittances Granger-cause changes in the informal sector's size.
- Political stability dynamics: Political stability interacts with remittances to jointly Granger-cause the informal sector. Additionally, there is a reciprocal causality between remittances and political stability, indicating a mutual influence within the economic-political nexus.

3.6.3.2. Long-term analysis

- Persistence of remittance effects: The influence of remittances on the informal sector remains robust even in the long term.
- Diminishing influence of political stability: Over extended periods, political stability's direct influence on remittances dissipates, underscoring possible adaptation or equilibration effects within political systems.

3.6.3.3. Discussion

The findings suggest that remittances contribute to the size and dynamics of the informal sector in OECD countries. Unlike in developing countries, where the informal sector often arises from necessity, in OECD countries, it may reflect strategic economic choices influenced by remittance inflows. Moreover, the reciprocal relationship between remittances and political stability highlights the economic contributions to political conditions.

3.6.3.4. Contextual factors in OECD countries:

The data provided is specifically for OECD countries. This context is important when interpreting the results because:

- **OECD countries** tend to have more developed economies compared to the global average. This can influence the nature of the informal sector and the role of remittances. The informal sector in OECD countries might be more involved in services or niche goods production, rather than basic needs as in developing countries. Remittances in OECD countries might be used for different purposes compared to developing countries, potentially including investment in established businesses, or supporting family members pursuing education or starting businesses within the informal sector.

- **Political stability** is generally higher in OECD countries on average. This can affect the relationship between political stability and the informal sector. A more stable political environment might lead to a smaller informal sector as businesses are incentivized to formalize. However, even in stable OECD countries, political changes or specific policies might still influence the size and characteristics of the informal sector.

3.6.3.5. Implications for policy and research

- Policy directions:

Sector-specific strategies: Policies aimed at managing the informal sector must consider its unique characteristics in OECD contexts, potentially focusing on formalization incentives and regulatory adjustments.
Remittance management: Understanding the cyclical nature of remittances and their impact on both the economy and political stability can help in crafting balanced fiscal and monetary policies.

- Research recommendations:

Further Causal Analysis: Additional studies should aim to unpack the underlying mechanisms of these relationships, perhaps through mixed methods approaches that incorporate qualitative data.

Comparative Studies: Examining these dynamics across different OECD sub-regions could illuminate diverse economic behaviours and policy outcomes.

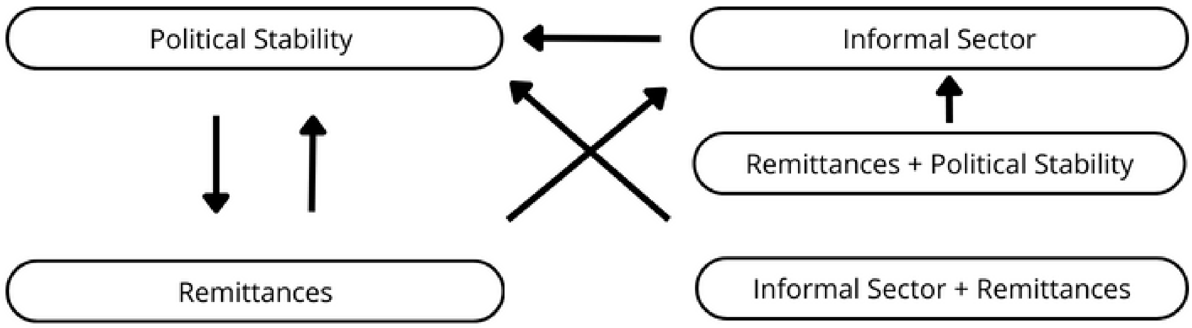
In addition, variations within OECD countries: There might be significant variations within the OECD group. Economic development levels, political systems, and cultural factors can all influence the relationships between remittances, political stability, and the informal sector.

Direction of causality: While the Granger causality test suggests remittances influence the informal sector, it's important to remember that causality can run in both directions. A larger informal sector might also attract more migrant workers who send remittances back home. While a majority of OECD countries are net recipients of migrants, they are also net senders of remittances. To explore this aspect, we have collected data on outward remittances from OECD countries. We have used these outward remittances as a proxy for inward migration. These results are provided and discuss in the next section.

This comprehensive analysis underscores the significant yet complex roles that remittances play in shaping the informal sector and influencing political stability within OECD countries. The insights garnered here should inform both scholarly discourse and policy debates, aiming to harness the potential benefits of remittances while mitigating associated risks. Further research is crucial to refine our understanding and to substantiate these findings across broader contexts and extended time frames.

Figure 3.3

Causal interactions: Informal sector, remittances, and political stability in OECD countries (lag 2)



3.6.4. Remittances paid and migration dynamics in OECD countries: An in-depth analysis

In an increasingly globalized world, the flow of remittances and migration has significant economic and social impacts, particularly within OECD countries which are characterized by complex interdependencies between developed and developing economies. This section explores the intricacies of outward remittances used as a proxy for inward migration, examining their relationships with the informal sector and political stability in regions like the USA/Canada and EU/UK.

Data on outward remittances was collected from world bank database. Granger causality tests were applied to assess the predictive power of one variable over another across multiple time lags.

The specific lags considered ranged from 1 to 5 years, providing insights into both immediate and delayed effects (Table 3.10 to 3.14).

3.6.4.1. Short-term dynamics (Lag 1):

The analysis at this stage did not reveal any significant causal relationships among the variables, indicating that the immediate effects of remittances on the informal sector and political stability are minimal or delayed.

3.6.4.2. Medium to long-term dynamics (Lags 2 to 5)

- Informal sector influence on remittances and political stability: The size of the informal sector consistently predicts outward remittances and political stability, with p-values indicating strong statistical significance (0.003 and 0.001 at lag 2, respectively).

  These results suggest that a larger informal sector, possibly indicative of economic underdevelopment or regulatory gaps, drives higher remittance outflows. This could be due to increased economic pressures or as a coping mechanism for economic disparities.
- Lack of reciprocal causality between migration and political stability: No evidence was found that outward remittances influence the informal sector size or political stability, suggesting that the causal pathway is predominantly one-directional from the informal

sector. This one-way relationship highlights the potential of the informal sector as a precursor to changes in migration patterns and political dynamics rather than a consequence of these factors.

3.6.4.3. Interpretation and policy implications

- Economic and social impacts of the informal sector: The findings that the informal sector drives remittance flows suggest that individuals might be relying on informal employment to meet financial obligations, both domestically and abroad. A significant informal sector might also reflect social inequities or inadequate economic integration, which could fuel political discontent or instability.
- Policy recommendations: Policies aimed at reducing the size of the informal sector through formalization could also decrease outward remittances—used as a proxy for inward migration— and enhance economic stability. Given the lack of direct impact of migration on political stability, economic policies should aim at broader socio-economic reforms to address underlying issues of inequality and economic disparity. While controlling migration flows alone may not influence political stability directly, well-rounded migration policies that include economic integration for migrants could indirectly stabilize political environments by reducing the reliance on the informal sector.

The complex interplay between outward remittances, the informal sector, and political stability in OECD countries underscores the need for comprehensive and integrated policy approaches that consider economic, social, and political factors. The Granger causality results point towards the informal sector as a key element in understanding and managing the dynamics of migration and political stability. Further research is essential to unravel the underlying mechanisms and to ensure that policies are effectively tailored to the unique challenges and opportunities within OECD countries.

3.6.5. Analysis of remittance dependence and economic dynamics in high remittance-to-GDP ratio countries

There might be significant variations within each large geopolitical set. Remittance dependence[3] can influence the relationships between remittances, political stability, and the informal sector. To address this possibility, this section analyzes the influence of remittances on the informal sector and political stability in countries with a remittance-to-GDP ratio exceeding the OECD average of 0.84%[4]. By utilizing a panel VAR-Granger causality model, we assess the dynamics among remittances, the informal sector size, and political stability, focusing on countries heavily dependent on remittances.
Countries with a remittance-to-GDP ratio above 0.84% were selected to highlight the impact of high remittance inflows. A panel VAR-Granger causality test was employed to determine the predictive relationships among the variables over selected time lags.

3.6.5.1. Results and analysis

- Remittances and economic activity: There is a strong Granger-causal relationship from the size of the informal sector in the past (loginf) to current remittances (p-value = 0.000), indicating a significant predictive power of past informal sector activities on current remittance volumes. Political stability shows a weaker influence on remittances (p-value = 0.168), suggesting potential, albeit non-significant, causal effects at the 5% level.
- Impact on the informal sector: Past remittances significantly Granger-cause the size of the informal sector (p-value = 0.019), implying that fluctuations in remittances can predict changes in the informal sector size. No significant causal influence from political stability to the informal sector was detected (p-value = 0.380).
- Political Stability Dynamics: Neither remittances nor the informal sector size show significant Granger-causal effects on political stability (both p-values above 0.48), indicating that these economic variables do not predict changes in political conditions.

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[3] Economic development levels, political systems, and cultural factors can all influence the relationships between remittances, political stability, and the informal sector.
[4] We analyze the impact of remittances on the informal sector and political stability in countries with high remittance dependence defined as a remittance-to-GDP ratio exceeding the OECD average of 0.84% and the median of our sample evaluated to 1.45%. We found the same results.

3.6.5.2. Interpretation and Contextualization

The results underscore a strong linkage between remittances and the informal sector in countries with high remittance dependence. This suggests that remittances are a pivotal factor in driving economic activities, particularly within the informal sector, which might include activities from self-employment to small-scale enterprises that do not formally register their economic contributions.

The lack of significant causal links from remittances or the informal sector to political stability suggests that while economic factors are crucial, they do not directly translate into political changes in these contexts. This may indicate that political dynamics are influenced by other structural or external factors.

Given the significant role of remittances in supporting the informal sector, policies aimed at enhancing the productive use of remittances could foster more sustainable economic development. This could involve measures to facilitate greater financial inclusion, improve investment opportunities for remittance funds, or provide better support systems for small and informal businesses.

The potential, albeit weak, influence of political stability on remittances highlights the need for stable governance structures that can enhance economic confidence and possibly influence economic behaviors related to remittance flows.

The weak link between political stability and remittances requires additional exploration to fully understand the nuances of this relationship. Further studies could also assess the impact of different model specifications, lag structures, and include more nuanced socio-economic variables to broaden the understanding of these dynamics.

The analysis provides crucial insights into the dynamics of remittances, the informal sector, and political stability in countries heavily dependent on remittances. The findings highlight the importance of remittances in shaping economic conditions, particularly within the informal sector, and indicate that political factors may not directly influence these economic outcomes. Continued research is essential to delve deeper into these relationships and to guide effective policy-making that leverages remittances for economic development while ensuring political stability.

3.7. Conclusion

This study used the PVAR model and the Granger causality test to analyse the subtle relationship between the informal sector, political stability, and remittances in four large geopolitical sets (MENA and SSA, Latin America and OECD countries) using data from 1996 to 2017.

The findings offer a compelling overview of the dynamics between remittances, the informal sector, and political stability across these regions. Specifically, the study shows how remittances significantly boost the informal sector's size in the short term, particularly in the MENA, Sub-Saharan Africa, and Latin America. This relationship, characterized by Granger causality, indicates that remittances are a predictive factor for changes in the informal sector, often reflecting the sector's expansion due to funding of informal activities and increased demand for goods and services. Notably, the impact of political stability on the informal sector appears negligible, suggesting that remittances play a more decisive role in the immediate economic adjustments within these regions.

In MENA and Sub-Saharan Africa, the influence of remittances on the informal sector diminishes over time, revealing that their immediate effect primarily addresses on basic needs rather than long-term business investment. The absence of a strong causal relationship between political stability and the informal sector highlights the region's resilience to political fluctuations, with the informal sector as an adaptive mechanism.

Latin America presents a unique case with a bidirectional relationship between remittances and the informal sector, suggesting a complex, interdependent interaction. However, like in other regions, this influence wanes beyond the short term, underscoring the transient nature of remittances' impact.

The OECD countries show a sustained influence of remittances on the informal sector over longer periods, unlike the developing regions. This persistence may reflect the different roles remittances play in more developed economies, potentially influencing more strategic economic decisions rather than mere survival strategies.

This comprehensive analysis highlights the need for tailored policy responses that consider the temporal and regional dynamics of remittances and their broader economic implications. Future research should focus on further exploring the underlying mechanisms of these relationship, employing both qualitative and quantitative methods to gain a deeper understanding of how remittances can be leveraged for sustainable economic development and stability in diverse geopolitical contexts.

Synthetic Table of Identified Causalities by Region

Legend :

Causality	MENA and SSA	Latin America	OECD	OECD Remittances Paid (Migration)	Remittances/GDP > 0.84%
Remittances → Informal Sector	**YES**	**YES**	**YES**	NO	**YES**
Informal Sector → Remittances	NO	**YES**	NO	**YES**	**YES**
Political Stability → Remittances	NO	NO	**YES**	NO	NO
Remittances + Political Stability → Informal Sector	**YES**	**YES**	**YES**	NO	**YES**
Political Stability → Informal Sector	NO	NO	NO	NO	NO
Remittances → Political Stability	NO	NO	**YES**	NO	NO
Informal Sector → Political Stability	NO	NO	**YES**	**YES**	NO

- *YES: Causality identified in the study.*
- *NO: No causality identified in the study.*

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4. Conclusion générale de la thèse

La première partie de notre étude a clarifié certains aspects des relations complexes entre les investissements directs étrangers (IDE), le PIB et la stabilité politique dans la région MENA ainsi que dans les pays d'Afrique subsaharienne. Les résultats montrent que l'IDE est fortement corrélé à la stabilité politique et au PIB, mais il n'est pas causé directement par ces facteurs pour l'ensemble des pays étudiés. Une analyse comparative entre les pays du Moyen Orient et ceux d'Afrique subsaharienne révèle des types de causalités différents. En Afrique subsaharienne, l'IDE influence positivement le PIB et la stabilité politique, tandis que les relations causales restent ambiguës au Moyen-Orient. Cette étude met en lumière l'importance de considérer les circonstances politiques et sociologiques spécifiques à chaque région avant de généraliser des résultats.

Les résultats de cette partie révèlent également une relation solide entre l'Aide Publique au Développement, les remittances, la croissance économique et les efforts de lutte contre la corruption, notamment dans les régions MENA et d'Afrique subsaharienne. Une augmentation du PIB attire davantage d'Aide Publique, et l'aide au développement et les remittances apparaissent comme complémentaires, favorisant un développement durable et la réduction de la corruption, créant un cycle vertueux et dynamique. Cette étude souligne l'importance de gérer ces flux financiers comme des outils complémentaires pour promouvoir la résilience économique et le développement à long terme, en particulier dans des zones politiquement et économiquement instables.

La deuxième partie de notre étude analyse la relation entre le secteur informel, la stabilité politique et les envois de fonds dans quatre grandes régions (MENA, Afrique subsaharienne, Amérique latine et pays de l'OCDE) sur la période 1996-2017. Les résultats montrent que les envois de fonds favorisent l'expansion du secteur informel à court terme, notamment dans les régions MENA, Afrique subsaharienne et Amérique latine. En revanche, la stabilité politique semble avoir un impact négligeable sur le secteur informel. L'influence des remittances diminue avec le temps dans les pays en développement, tandis qu'elle persiste plus longtemps dans les pays de l'OCDE.

Cette dernière étude, souligne l’importance de politiques adaptées aux dynamiques régionales des remittances pour favoriser un développement économique durable.

Ces conclusions mettent en lumière la complexité des relations économiques et politiques entre les régions étudiées et la nécessité d'approches politiques sur mesure pour optimiser le développement et réaliser les objectifs sociaux et économique à long terme.

1. Annexe chapitre 1

Table 1.1

GDP, FDI and Political Stability (GMM Estimation) (Lag 1)

Number Of observations: 382
Number of panels: 32
Ave. No. Of T: 11.938

	LogGDP		
	LogGDP	LogFDI	StdPS
	Lag1	Lag1	Lag1
Coef.	0.8531814	0.0277605	0.0502559
Std. Err.	0.0251866	0.0079574	0.0316724
z	33.87***(0.000)	3.49***(0.000)	1.59(0.113)
95% Conf.	0.8038165	0.0121643	-0.0118208
Interval	0.9025463	0.0433567	0.1123326

	LogFDI		
	LogGDP	LogFDI	StdPS
	Lag1	Lag1	Lag1
Coef.	-0.062473	0.5725525	-0.211847
Std. Err.	0.1486912	0.1056044	0.2139589
z	-0.42(0.674)	5.42***(0.000)	-0.99(0.322)
95% Conf.	-0.3539025	0.3655716	-0.6311987
Interval	0.2289564	0.7795333	0.2075047

	StdPS		
	LogGDP	LogFDI	StdPS
	Lag1	Lag1	Lag1
Coef.	-0.0216523	-0.0216744	0.8955157
Std. Err.	0.0474626	0.0253758	0.0620792
z	-0.46(0.648)	-0.85(0.393)	14.43***(0.000)
95% Conf.	-0.1146773	-0.0714101	0.7738427
Interval	0.0713726	0.0280613	1.017189

*Note: Signif. codes *** $p<0.001$, ** $p<0.01$, * $p<0.05$*

Table 1.2

GDP, FDI and Political Stability (GMM Estimation) (Lag 2)

Number Of observations: 340
Number of panels: 32
Ave. No. Of T: 10.625

	LogGDP					
	LogGDP		LogFDI		StdPS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.9203867	-0.0654642	0.0258404	-0.000206	0.0771008	-0.0266206
Std. Err.	0.1627713	0.1195241	0.0082872	0.0078835	0.0365146	0.0214486
z	5.65***(0.000)	-0.55(0.584)	3.12**(0.002)	-0.03(0.979)	2.11*(0.035)	-1.24(0.215)
95% Conf.	0.6013607	-0.2997272	0.0095978	-0.0156574	0.0055335	-0.0686591
Interval	1.239413	0.1687988	0.042083	0.0152454	0.1486681	0.0154178

	LogFDI					
	LogGDP		LogFDI		StdPS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	-0.1648594	0.0274646	0.5024839	0.0810821	0.073137	-0.0178671
Std. Err.	0.8391439	0.6277877	0.131694	0.1004175	0.311919	0.2778613
z	-0.2(0.844)	0.04(0.965)	3.82***(0.000)	0.81(0.419)	0.23(0.815)	-0.06(0.949)
95% Conf.	-1.809551	-1.202977	0.2443684	-0.1157325	-0.538213	-0.5624653
Interval	1.479832	1.257906	0.7605994	0.2778968	0.6844869	0.5267311

	StdPS					
	LogGDP		LogFDI		StdPS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.4774475	-0.3495135	0.0206641	-0.0693398	0.8364644	0.0619305
Std. Err.	0.233304	0.1758199	0.0266845	0.0220023	0.0820704	0.0754363
z	2.05*(0.041)	-1.99*(0.047)	0.77(0.439)	-3.15**(0.002)	10.19***(0.000)	0.82(0.412)
95% Conf.	0.02018	-0.6941142	-0.0316365	-0.1124635	0.6756093	-0.0859219
Interval	0.9347149	-0.0049129	0.0729646	-0.0262162	0.9973194	0.2097829

*Note: Signif. codes *** p<0.001, ** p<0.01, * p<0.05*

Table 1.3

GDP, FDI and Political Stability (Granger-Causality Test)

Lag(1)

Equation \ Excluded	LogGDP			LogFDI			StdPS		
	LogFDI	StdPS	ALL	LogGDP	StdPS	ALL	LogGDP	LogFDI	ALL
chi2	12.171	2.518	16.212	0.177	0.98	0.981	0.208	0.73	1.51
Df	1	1	2	1	1	2	1	1	2
Prob > chi2	0	0.113	0	0.674	0.322	0.612	0.648	0.393	0.47

Lag(2)

Equation \ Excluded	LogGDP			LogFDI			StdPS		
	LogFDI	StdPS	ALL	LogGDP	StdPS	ALL	LogGDP	LogFDI	ALL
chi2	9.85	4.691	12.362	0.557	0.078	0.832	4.189	10.118	13.984
Df	2	2	4	2	2	4	2	2	4
Prob > chi2	0.007	0.096	0.015	0.757	0.962	0.934	0.123	0.006	0.007

PVAR lag length test

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.9999146	25.87729	0.5254188	-124.6733	-28.12271	-66.91969
2	0.9999259	16.14299	0.5825686	-84.22409	-19.85701	-45.72166
3	0.9999105	11.95471	0.2158746	-38.22883	-6.04529	-18.97762

The above table provide statistical metrics for selecting the optimal lag in a time-series analysis specifically for the Sub-Saharan Africa (SSA) and Middle East and North Africa (MENA) regions. Each lag indicates how far back in time the variables are being analyzed to predict future values. Here's a breakdown of the columns and what each metric represents:

Columns Explanation

- Lag: The number of time periods used to shift the data for the analysis.
- CD (Cross-correlation Decay): Indicates the degree to which correlations between variables decrease as the lag increases. Values close to 1 suggest little decay, indicating that earlier data points remain highly relevant.
- J: The test statistic value for a specific test (not specified but often related to testing for serial correlation or another time-series property).
- J pvalue: P-value associated with the J test statistic, indicating the probability of observing the test results under the null hypothesis.
- MBIC (Modified Bayesian Information Criterion): A criterion for model selection among a finite set of models; lower values indicate better models, with adjustments to penalize more complex models.
- MAIC (Modified Akaike Information Criterion): Similar to MBIC, it's another model selection criterion that penalizes less harshly for model complexity.
- MQIC (Modified Hannan-Quinn Information Criterion): Also used for model selection, providing a balance between MBIC and MAIC in terms of penalizing model complexity.

Interpretation and Selection of Optimal Lag

- CD (Cross-correlation Decay): Across all lags, the CD value is very close to 1, indicating that correlations are maintained even with increasing lags, suggesting a strong persistent relationship in the data across time periods.
- J and J p-value: Lower J values and higher p-values (as seen from lag 1 to 3) suggest decreasing statistical significance in terms of the model's ability to predict future values based on past values. This implies that as you incorporate more past data (increasing lag), it becomes less statistically significant in explaining future variations.

- Information Criteria (MBIC, MAIC, MQIC):

Lag 1: Offers the lowest (most negative) values for MBIC, MAIC, and MQIC, suggesting that it provides the best fit among the tested models with the least penalty for model complexity.

Lag 2 and 3: Show increasing values in MBIC, MAIC, and MQIC, indicating that adding more lags leads to models that fit worse, even after adjusting for complexity.

Given this data, Lag 1 is the optimal choice for analyzing time-series data in SSA and MENA for this study. It provides the best balance between model fit and complexity according to the information criteria and maintains statistical significance according to the J statistic and its associated p-value. This suggests that looking one period back provides the most relevant and significant insight into future values without unnecessarily complicating the model with data that do not add predictive value.

Given the MBIC, MAIC, and MQIC values, along with the J p-values, the choice of Lag 1 can be economically justified as it offers a balance between capturing essential economic dynamics and maintaining model parsimony and robustness. This choice is particularly appropriate in the SSA and MENA context, where annual economic fluctuations are closely tied to national and international economic policies, and where economic modelling needs to remain adaptable and robust against frequent economic and political changes.

Table 1.4

FDI, GDP and Political Stability (Middle East countries)

panel VAR-Granger causality Wald test
Ho: Excluded variable does not Granger-cause Equation variable
Ha: Excluded variable Granger-causes Equation variable

Lag(1)

Equation \ Excluded	LogFDI			LogGDP			StdPS		
	LogGDP	StdPS	ALL	LogFDI	StdPS	ALL	LogFDI	LogGDP	ALL
chi2	2.732	1.371	2.793	2.819	2.765	6.222	0.47	0.217	0.47
df	1	1	2	1	1	2	1	1	2
Prob > chi2	0.098	0.242	0.247	0.093	0.096	0.045	0.493	0.641	0.791

Lag(2)

Equation \ Excluded	LogFDI			LogGDP			StdPS		
	LogGDP	StdPS	ALL	LogFDI	StdPS	ALL	LogFDI	LogGDP	ALL
chi2	2.421	0.382	3.503	2.412	3.641	5.682	0.487	1.65	1.651
Df	2	2	4	2	2	4	2	2	4
Prob > chi2	0.298	0.826	0.477	0.299	0.162	0.224	0.784	0.438	0.8

PVAR Lag Length test

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.999982	32.56248	0.2118929	-73.06214	-21.43752	-41.09647
2	0.9999891	13.87752	0.7370399	-56.53889	-22.12248	-35.22845
3	0.999958	9.355008	0.40517	-25.8532	-8.644992	-15.19798

Table 1.5

FDI, GDP and Political Stability (African countries)

panel VAR-Granger causality Wald test
Ho: Excluded variable does not Granger-cause Equation variable
Ha: Excluded variable Granger-causes Equation variable

Lag (1)

Equation \ Excluded	LogFDI			LogGDP			StdPS		
	LogGDP	StdPS	ALL	LogFDI	StdPS	ALL	LogFDI	LogGDP	ALL
chi2	0.158	0.187	0.58	7.574	7.889	17.55	0.578	0.614	1.715
df	1	1	2	1	1	2	1	1	2
Prob > chi2	0.691	0.665	0.748	0.006	0.005	0	0.447	0.433	0.424

Lag(2)

Equation \ Excluded	LogFDI			LogGDP			StdPS		
	LogGDP	StdPS	ALL	LogFDI	StdPS	ALL	LogFDI	LogGDP	ALL
chi2	0.013	0.391	0.452	9.606	7.78	14.259	11.125	1.725	13.133
Df	2	2	4	2	2	4	2	2	4
Prob > chi2	0.994	0.822	0.978	0.008	0.02	0.007	0.004	0.422	0.011

PVAR Lag Length test

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.999896	22.22986	0.725607	-122.6515	-31.77014	-68.49436
2	0.9999105	12.74963	0.806227	-83.83794	-23.25037	-47.73319
3	0.9998887	9.11155	0.4270415	-39.18223	-8.88845	-21.12986

Table 1.6

FDI vs Political Stability (Iraq case)

panel VAR-Granger causality Wald test
Ho: Excluded variable does not Granger-cause Equation variable
Ha: Excluded variable Granger-causes Equation variable

Lag(1)

Equation \ Excluded	StdPS		LogFDI	
	LogFDI	ALL	StdPS	ALL
chi2	0.161	0.161	4.843	4.843
df	1	1	1	1
Prob > chi2	0.688	0.688	0.028	0.028

Lag(2)

Equation \ Excluded	StdPS		LogFDI	
	LogFDI	ALL	StdPS	ALL
chi2	0.457	0.457	17.553	17.553
Df	2	2	2	2
Prob > chi2	0.796	0.796	0	0

Table 1.7

FDI vs Political Stability (Lebanon case)

panel VAR-Granger causality Wald test
Ho: Excluded variable does not Granger-cause Equation variable
Ha: Excluded variable Granger-causes Equation variable

Lag(1)

Equation \ Excluded	StdPS		LogFDI	
	LogFDI	ALL	StdPS	ALL
chi2	0.367	0.367	0.407	0.407
df	1	1	1	1
Prob > chi2	0.545	0.545	0.523	0.523

Lag(2)

Equation \ Excluded	StdPS		LogFDI	
	LogFDI	ALL	StdPS	ALL
chi2	0.025	0.025	6.13	6.13
Df	2	2	2	2
Prob > chi2	0.988	0.988	0.047	0.047

Table 1.8

FDI vs Political Stability (Algeria case)

panel VAR-Granger causality Wald test
Ho: Excluded variable does not Granger-cause Equation variable
Ha: Excluded variable Granger-causes Equation variable

Lag(1)

Equation \ Excluded	StdPS		LogFDI	
	LogFDI	ALL	StdPS	ALL
chi2	0.238	0.238	0.639	0.639
Df	1	1	1	1
Prob > chi2	0.626	0.626	0.424	0.424

Lag(2)

Equation \ Excluded	StdPS		LogFDI	
	LogFDI	ALL	StdPS	ALL
chi2	4.726	4.726	6.88	6.88
Df	2	2	2	2
Prob > chi2	0.094	0.094	0.032	0.032

Table 1.9

Collinearity test (with GDP as dependent variable)

Variable	VIF	SQRT VIF	Tolerance	R-Squared
StdPS	1.00	1.00	0.9997	0.0003
LogFDI	1.00	1.00	0.9997	0.0003
Mean VIF	1.00			

	Eigenval	Cond Index
1	1.0172	1.0000
2	0.9828	1.0174
Condition Number		1.0174

Note: Eigenvalues and Cond Index computed from deviation sscp (no intercept)

Det(correlation matrix)   0.9997

Table 1.10

Collinearity test (with FDI as dependent variable)

Variable	VIF	SQRT VIF	Tolerance	R-Squared
StdPS	1.05	1.02	0.9548	0.0452
LogGDP	1.05	1.02	0.9548	0.0452
Mean VIF	1.05			

	Eigenval	Cond Index
1	1.2127	1.0000
2	0.7873	1.2410
Condition Number		1.2410

Note: Eigenvalues and Cond Index computed from deviation sscp (no intercept)

Det(correlation matrix) 0.9548

Table 1.11

Collinearity test (with PS as dependent variable)

Variable	VIF	SQRT VIF	Tolerance	R-Squared
LogGDP	2.40	1.55	0.4169	0.5831
LogFDI	2.40	1.55	0.4169	0.5831
Mean VIF	2.40			

	Eigenval	Cond Index
1	1.7636	1.0000
2	0.2364	2.7316
Condition Number		2.7316

Note: Eigenvalues and Cond Index computed from deviation sscp (no intercept)

Det(correlation matrix) 0.4169

Table 1.12

Collinearity test (regress method)

Source	SS	df	MS
Model	1247.23068	2	623.615338
Residual	813.599349	456	1.7842091
Total	2060.83003	458	4.49962888

Number of obs	=	459
F(2, 456)	=	349.52
Prob > F	=	0.0000
R-squared	=	0.6052
Adj R-squared	=	0.6035
Root MSE	=	1.3357

LogFDI	Coef.	Std. Err.	t	P>t	Beta
LogGDP	1.006694	0.038085	26.43	0.000	0.7959658
StdPS	0.3425563	0.0678428	5.05	0.000	0.1520473
_cons	-3.768688	0.882873	-4.27	0.000	0.0

Table 1.13

The Variance inflation factors (VIF)

The Variance inflation factors (VIF) range from 1 upwards. The numerical value for VIF tells you (in decimal form) what percentage the variance is inflated for each coefficient. For example, a VIF of 1.9 tells that the variance of a particular coefficient is 90% bigger than what you would expect if there was no multicollinearity
if there was no correlation with other predictors.

A **rule of thumb** for interpreting the variance inflation factor:

- 1 = not correlated.
- Between 1 and 5 = moderately correlated.
- Greater than 5 = highly correlated.

$$VIF = \frac{1}{1 - R_i^2}$$

Table 1.14

Collinearity test (GDP as dependent variable)

Variable	VIF	SQRT VIF	Tolerance	R-Squared
LogFDI	1.00	1.00	0.9975	0.0025
FDIPS	1.00	1.00	0.9975	0.0025
Mean VIF	1.00			

	Eigenval	Cond Index
1	2.0039	1.0000
2	0.9903	1.4225
3	0.0058	18.5382
Condition Number		18.5382

Note: Eigenvalues and Cond Index computed from scaled sscp (w/ intercept)

Det(correlation matrix) 0.9975

Table 1.15

Collinearity test (PS as dependent variable)

Variable	VIF	SQRT VIF	Tolerance	R-Squared
LogFDI	11.27	3.36	0.0888	0.9112
FDIGDP	11.27	3.36	0.0888	0.9112
Mean VIF	1.00			

	Eigenval	Cond Index
1	2.9852	1.0000
2	0.0141	14.5466
3	0.0007	66.5071
Condition Number		66.5071

Note: Eigenvalues and Cond Index computed from scaled sscp (w/ intercept)

Det(correlation matrix) 0.0888

Table 1.16

Matrix correlation

	LogFDI	LogGDP	StdPS
LogFDI	1.0000		
LogGDP	0.7636	1.0000	
StdPS	-0.0172	-0.2127	1.0000

Table 1.17

List of samples countries

1 - Algeria	11 - Guinea-Bissau	21 - Nigeria	31 - West Bank and Gaza
2 - Benin	12 - Iraq	22 - Oman	32 - Zambia
3 - Burundi	13 - Jordan	23 - Rwanda	
4 - Central African Republic	14 - Lebanon	24 - Senegal	
5 - Chad	15 - Liberia	25 - Somalia	
6 - Congo. Dem. Rep.	16 - Libya	26 - Sudan	
7 - Djibouti	17 - Malawi	27 - Syrian Arab Republic	
8 - Egypt. Arab Rep.	18 - Mali	28 - Togo	
9 - Eritrea	19 - Mauritania	29 - Tunisia	
10 - Gambia. The	20 - Mozambique	30 - Uganda	

Table 1.18

Stationarity test: Eigenvalue stability condition

The Eigenvalue stability condition provide the part of the stability analysis for a Panel Vector Autoregression (PVAR) model. This analysis is crucial for assessing whether the model is dynamically stable and whether the inferences drawn from it about the long-term relationships and impacts are valid. Here is what the table means and its implications:

Understanding Eigenvalues in PVAR Stability

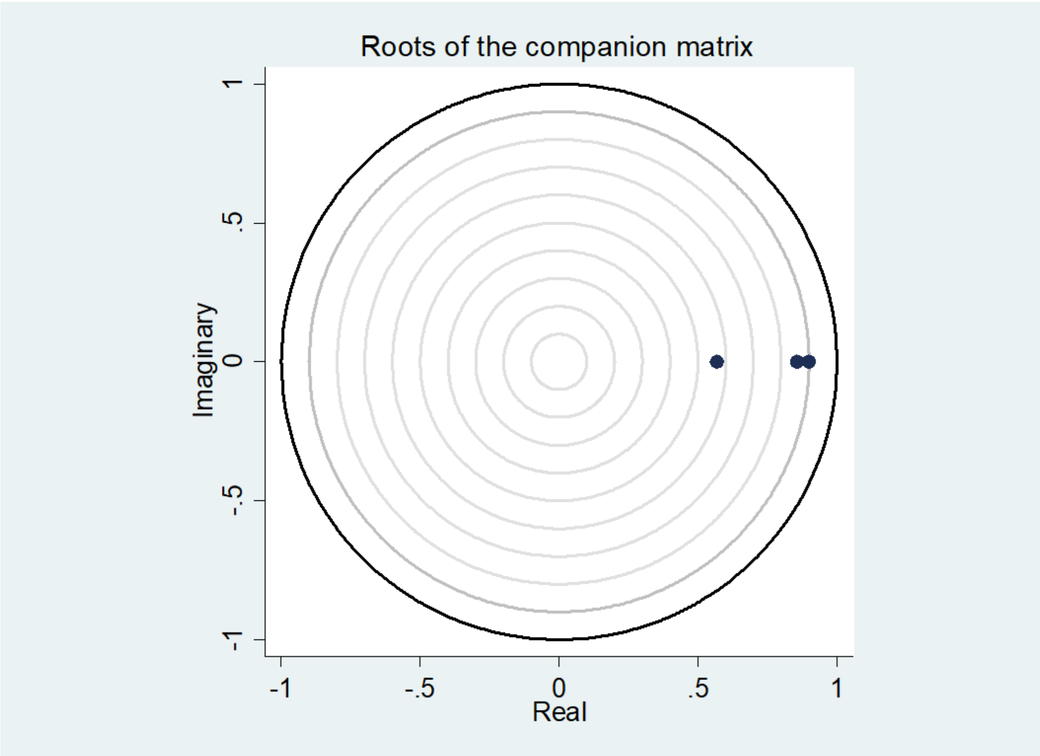
- Eigenvalue: Each eigenvalue of the model's companion matrix indicates the stability of a particular dynamic process within the PVAR system. The eigenvalue is composed of a real part and an imaginary part, with the modulus (absolute value) reflecting the distance of the eigenvalue from the origin in the complex plane.
- Real Part: Indicates the speed of the response in the system. A real part closer to 1 indicates a slower decay of the effect of shocks.
- Imaginary Part: Indicates the oscillatory behavior of the system. A non-zero imaginary part suggests cyclical behavior.
- Modulus: The critical measure for stability. For the PVAR model to be stable, the modulus of each eigenvalue must be less than 1.

Given our model's stability, we can proceed with analyzing the dynamic responses of these variables to different shocks (e.g., through impulse response functions) or conduct scenario analyses to explore how changes in one variable might have effects on others over time. This kind of analysis can be particularly useful for examining the impacts of potential policy changes or external economic shocks.

Stationary test: Eigenvalue stability condition

Eigenvalue		
Real	Imaginary	Modulus
0.8984669	0	0.8984669
0.8560005	0	0.8560005
0.5667822	0	0.5667822

All the eigenvalues lie inside the unit cercle.
pVAR satisfies stability condition.



Interpretation of Results

- The eigenvalues presented are 0.8984669, 0.8560005, and 0.5667822. All these values are less than 1.
- **Stability**: Since all eigenvalues have moduli less than 1, this indicates that the PVAR model satisfies the stability condition. This is a good sign as it implies that the impacts of shocks to the variables in the model will dissipate over time rather than increase or oscillate indefinitely.

Implications

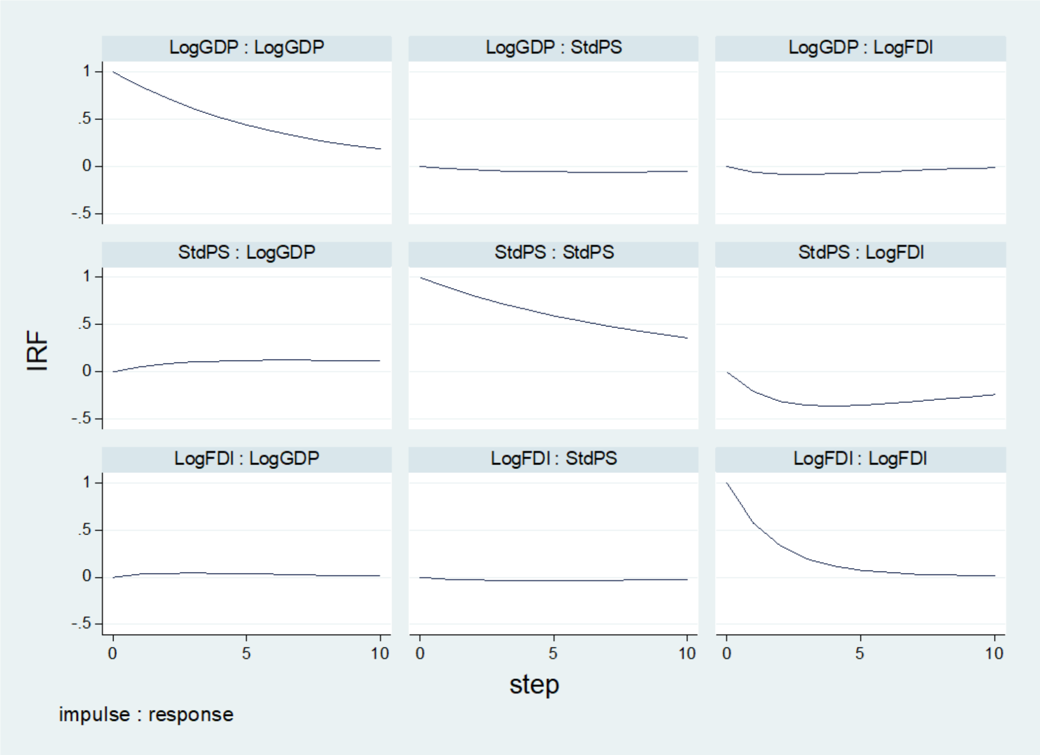
- **Model Dynamics**: The model is stable, suggesting that it appropriately captures the dynamics among the variables (log of informal sector size, log of remittances, and political stability) without leading to explosive predictions.
- **Forecasting and Inference**: Stability ensures that the model can be used for forecasting and policy inference within the bounds of the data and model specifications used, without concerns about the results diverging over time.

The graphical above represents these results, usually displayed in a root locus plot, visually confirm that the eigenvalues are within the unit circle.

Table 1.19

Forecast-error variance decomposition

Response variable and Forecast horizon			Impulse variable		
			LogFDI	StdPS	LogGDP
	LogFDI	0	0	0	0
		1	1	0	0
		2	0.9966768	0.0032751	0.000048
		3	0.9902617	0.0096134	0.0001249
		4	0.9823368	0.174614	0.0002018
		5	0.974202	0.0255345	0.0002635
		6	0.9666211	0.330722	0.0003067
		7	0.959926	0.0397402	0.0003338
		8	0.9541917	0.0454593	0.0003491
		9	0.949367	0.0502764	0.0003567
		10	0.9453499	0.0542904	0.0003596
	StdPS	0	0	0	0
		1	0.0009164	0.9990836	0
		2	0.0016807	0.9982736	0.0000458
		3	0.0041977	0.9956732	0.0001292
		4	0.0070481	0.992718	0.0002338
		5	0.0097047	0.9899462	0.000349
		6	0.120108	0.9875216	0.0004677
		7	0.0139537	0.985461	0.0005853
		8	0.0155707	0.9837305	0.0006988
		9	0.0169109	0.9822832	0.000806
		10	0.0180211	0.9810731	0.0009057
	LogGDP	0	0	0	0
		1	0.042197	0.028828	0.928975
		2	0.1017767	0.0509872	0.8472361
		3	0.1459222	0.0723105	0.7817673
		4	0.1746835	0.0923375	0.7329789
		5	0.1921794	0.1110625	0.6967581
		6	0.2021181	0.1284929	0.6693889
		7	0.2071808	0.1446027	0.6482165
		8	0.2091883	0.1593573	0.6314544
		9	0.209347	0.172738	0.6179151
		10	0.2084443	0.1847536	0.606802



The figure above show Impulse Response Function (IRF) graphs for the Sub-Saharan Africa and MENA region. Impulse Response Functions (IRFs) describe how one variable in a system responds to a shock or impulse in another variable over time. This is crucial in time-series analysis, particularly in Vector Autoregression (VAR) or Panel Vector Autoregression (PVAR) models, as it helps understand the dynamic effects of shocks across variables.

Given the dimensions and brief description, the IRFs seem to plot the response of each variable to shocks in each of the other variables across different time steps (0 to 10). Each row and column in the IRF plots likely represents:

- Columns (Impulse Variables): The source of the shock (e.g., LogGDP, LogFDI, StdPS).
- Rows (Response Variables): The variables whose responses to the shocks are being measured (e e.g., LogGDP, LogFDI, StdPS).

Steps to Analyze the IRFs:

- Identify the Nature of Shocks: Determine what a positive or negative shock in each impulse variable represents (e.g., increase in political stability, increase in remittances).
- Observe the Response Patterns: Look at how each response variable's graph changes over time following a shock:
    - Immediate vs. Delayed Responses: Does the variable respond immediately, or is there a lag?
    - Direction of Response: Does the variable increase or decrease in response to a shock?
    - Duration and Decay: How long does the response last, and how quickly does it return to baseline or stabilize?
    - Inter-variable Dynamics: Understand the interactions between variables. For example, how does an increase in remittances affect political stability and the informal sector?

Panel Descriptions and Interpretations

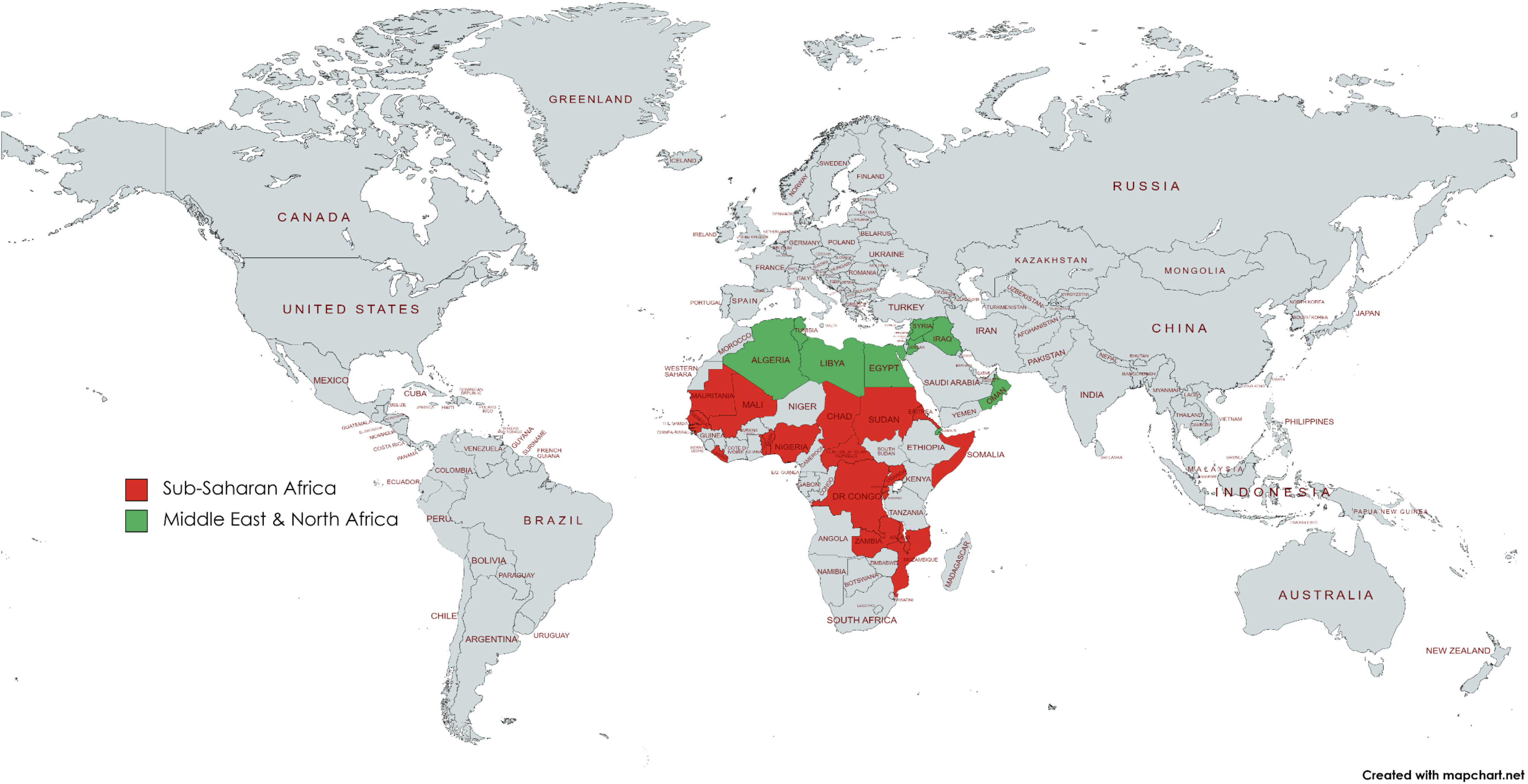
- **LogGDP Impulse Responses:**
    - **LogGDP→ LogGDP:** Shows a decline in response over time, starting from 1, which suggests that the effect of a shock to GDP on itself diminishes gradually.
    - **StdPS → LogGDP:** A small, initially flat response that begins to increase slightly, suggesting a delayed and modest positive effect of shocks in the political stability on GDP.
    - **LogFDI → LogGDP:** A small, initially flat response that begins to increase slightly, suggesting a delayed and modest positive effect of shocks in the FDI on GDP.
- **StdPS Impulse Responses:**
    - **LogGDP→ PS:** A negative response that gradually diminishes, indicating that a shock to political stability tends to reduce remittances initially, but this effect decreases over time.

  - **PS → PS:** Shows a decline in response over time, starting from 1, which suggests that the effect of a shock to political stability on itself diminishes gradually.
  - **LogFDI→ PS:** A slight increase over time, suggesting that a shock to the FDI has a progressively positive influence on PS.
- **LogFDI Impulse Responses:**
  - **LogGDP → LogFDI:** A negative and somewhat constant response, indicating a consistent negative effect of shocks in GDP on the FDI.
  - **PS→ LogFDI:** it starts by a decreasing response then slight decreasing , suggesting that shocks in PS have a growing positive effect on the FDI over time.
  - **LogFDI → LogFDI:** A negative response that gradually diminishes, indicating that a shock to the FDI tends to reduce itself.

These IRF plots provide valuable insights into the interconnectedness of political and economic sectors dynamics in the SSA and MENA regions. Policymakers could use this information to craft strategies that consider the implications of changes in one area on the others.

Figure 1.4

Cartography of sample countries



Number Of observations: 51
Number of panels: 6
Ave. No. Of T: 8.500

2. Annexe chapitre 2

Table 2.1

Aid, GDP and Remittances in the Middle East (GMM Estimation) (Lag 2)

	LogAid					
	LogAid		LogRem		LogGDP	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	-0.3711679	-0.3749265	-0.1213557	-0.0927762	-2.571168	-1.256311
Std. Err.	0.2564398	0.1894106	0.0425741	0.0904779	1.063434	0.765392
Z P>z	-1.45(0.148)	-1.98*(0.0148)	-2.85**(0.004)	-1.03(0.305)	-2.42*(0.016)	-1.64(0.101)
95% Conf.	-0.8737806	-0.7461644	-0.2047994	-0.2701095	-4.65546	-2.756452
Interval	0.1314448	-0.0036885	-0.037912	0.0845572	-0.4868761	0.2438297

	LogRem					
	LogAid		LogRem		LogGDP	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.0616833	0.0457802	-0.394923	-0.1277164	0.9666944	1.194428
Std. Err.	0.0486929	0.0431937	0.03621	0.0484876	0.4655574	0.3216944
Z (P>Z)	1.27(0.205)	1.06(0.289)	-10.91***(0.000)	-2.63**(0.008)	2.08*(0.038)	3.71***(0.000)
95% Conf.	-0.0337531	-0.0388779	-0.4658932	-0.2227503	0.0542188	0.5639186
Interval	0.1571197	0.1304382	-0.3239528	-0.0326825	1.87917	1.824938

	LogGDP					
	LogAid		LogRem		LogGDP	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.104825	0.0272961	-0.362968	0.793787	0.8151497	0.3331852
Std. Err.	0.0845309	0.0572538	0.153383	0.0347587	0.3070043	0.2643004
Z (P>Z)	1.24(0.215)	0.48(0.634)	-2.37*(0.018)	2.28*(0.022)	2.66**(0.008)	1.26(0.207)
95% Conf.	-0.0608526	-0.0849193	-0.0663594	-0.0112528	0.2134324	-0.184834
Interval	0.2705025	0.1395116	-0.0062342	0.1475045	1.416867	0.8512044

Table 2.2

Aid, GDP and Remittances in the Middle East (Granger Causality Test)

Equation \ Excluded	LogAid			LogRem			LogGDP		
	LogRem	LogGDP	ALL	LogAid	LogGDP	ALL	LogAid	LogRem	ALL
chi2	9.994	6.636	53.477	1.835	15.425	16.304	1.938	24.310	41.560
Df	2	2	4	2	2	4	2	2	4
Prob > chi2	0.007	0.036	0.000	0.399	0.000	0.003	0.379	0.000	0.000

Table 2.3

Stationarity test: Eigenvalue stability condition; Aid, GDP and Remittances (Lag 2)

The Eigenvalue stability condition provide the part of the stability analysis for a Panel Vector Autoregression (PVAR) model. This analysis is crucial for assessing whether the model is dynamically stable and whether the inferences drawn from it about the long-term relationships and impacts are valid. Here is what the table means and its implications:

Understanding Eigenvalues in PVAR Stability

- Eigenvalue: Each eigenvalue of the model's companion matrix indicates the stability of a particular dynamic process within the PVAR system. The eigenvalue is composed of a real part and an imaginary part, with the modulus (absolute value) reflecting the distance of the eigenvalue from the origin in the complex plane.
- Real Part: Indicates the speed of the response in the system. A real part closer to 1 indicates a slower decay of the effect of shocks.
- Imaginary Part: Indicates the oscillatory behavior of the system. A non-zero imaginary part suggests cyclical behavior.
- Modulus: The critical measure for stability. For the PVAR model to be stable, the modulus of each eigenvalue must be less than 1.

Given our model's stability, we can proceed with analyzing the dynamic responses of these variables to different shocks (e.g., through impulse response functions) or conduct scenario analyses to explore how changes in one variable might have effects on others over time. This kind of analysis can be particularly useful for examining the impacts of potential policy changes or external economic shocks.

Eigenvalue		
Real	Imaginary	Modulus
0.9119404	0	0.9119404
-0.0256595	0.5884734	0.5890325
-0.0256595	-0.5884734	0.5890325
-0.5179311	0	0.5179311
-0.1468158	0.4778187	0.4998656
-0.1468158	-0.4778187	0.4998656

All the eigenvalues lie inside the unit cercle.
pVAR satisfies stability condition.

Figure 2.3

Eigenvalue stability condition: Aid, GDP and Remittances (Lag 2)

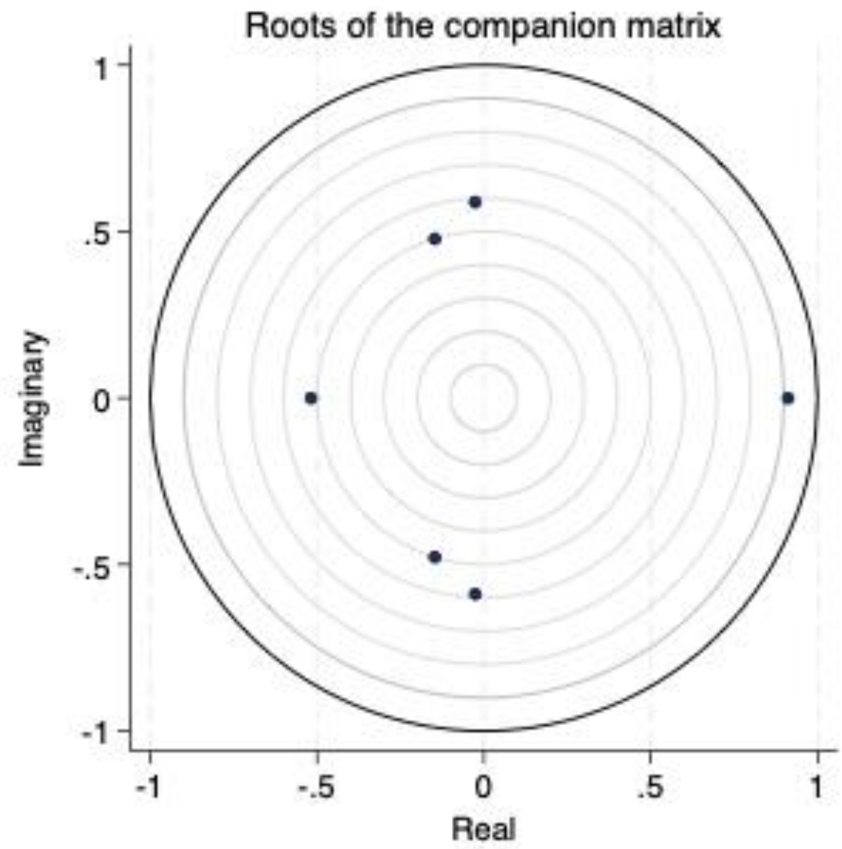


Table 2.4

Collinearity diagnostics: Aid, GDP and Remittances in the Middle East

The Variance inflation factors (VIF) range from 1 upwards. The numerical value for VIF tells you (in decimal form) what percentage the variance is inflated for each coefficient. For example, a VIF of 1.9 tells that the variance of a particular coefficient is 90% bigger than what you would expect if there was no multicollinearity
if there was no correlation with other predictors.

A **rule of thumb** for interpreting the variance inflation factor:

- 1 = not correlated.
- Between 1 and 5 = moderately correlated.
- Greater than 5 = highly correlated.

$$VIF = \frac{1}{1 - R_i^2}$$

Nb of observations : 69

Variable	VIF	SQRT VIF	Tolerance	R-Squared
LogAid	1.04	1.02	0.9640	0.0360
logRem	1.01	1.01	0.9880	0.0120
LogGDP	1.04	1.02	0.9579	0.0421
Mean VIF	1.03			

	Eigenval	Cond Index
1	1.6688	1.0000
2	1.0915	1.2365
3	0.9290	1.3403
4	0.3106	2.3179
Condition Number		2.3179

Note: Eigenvalues and Cond Index computed from scaled sscp (w/ intercept)

Det(correlation matrix) 0.9542

Table 2.5

Optimal lag in our PVAR model: *Aid, GDP and Remittances in the Middle East*

Number Of observations: 39
Number of panels: 5
Ave. No. Of T: 7.800

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.9842507	27.62999	0.4302347	-71.28618	-26.37001	-42.48555
2	0.9925046	17.32732	0.5007195	-0.48.61679	-18.67268	-29.41637
3	0.6727672	7.549391	0.5801142	-25.42266	-10.45061	-15.82245

The above table provide statistical metrics for selecting the optimal lag in a time-series analysis specifically for Middle East and North Africa (MENA) region. Each lag indicates how far back in time the variables are being analyzed to predict future values. Here's a breakdown of the columns and what each metric represents:

Columns Explanation

- Lag: The number of time periods used to shift the data for the analysis.
- CD (Cross-correlation Decay): Indicates the degree to which correlations between variables decrease as the lag increases. Values close to 1 suggest little decay, indicating that earlier data points remain highly relevant.
- J: The test statistic value for a specific test (not specified but often related to testing for serial correlation or another time-series property).
- J pvalue: P-value associated with the J test statistic, indicating the probability of observing the test results under the null hypothesis.
- MBIC (Modified Bayesian Information Criterion): A criterion for model selection among a finite set of models; lower values indicate better models, with adjustments to penalize more complex models.
- MAIC (Modified Akaike Information Criterion): Similar to MBIC, it's another model selection criterion that penalizes less harshly for model complexity.
- MQIC (Modified Hannan-Quinn Information Criterion): Also used for model selection, providing a balance between MBIC and MAIC in terms of penalizing model complexity.

Interpretation and Selection of Optimal Lag

- CD (Cross-correlation Decay): Across all lags, the CD value is very close to 1, indicating that correlations are maintained even with increasing lags, suggesting a strong persistent relationship in the data across time periods.
- J and J p-value: Lower J values and higher p-values (as seen from lag 1 to 3) suggest decreasing statistical significance in terms of the model's ability to predict future values based on past values. This implies that as you incorporate more past data (increasing lag), it becomes less statistically significant in explaining future variations.
- Information Criteria (MBIC, MAIC, MQIC):

Lag 1: Offers the lowest (most negative) values for MBIC, MAIC, and MQIC, suggesting that it provides the best fit among the tested models with the least penalty for model complexity.

Lag 2 and 3: Show increasing values in MBIC, MAIC, and MQIC, indicating that adding more lags leads to models that fit worse, even after adjusting for complexity.

Number Of observations: 51
Number of panels: 6
Ave. No. Of T: 8.500

Table 2.6

Remittances, Aid, GDP and Corruption in the Middle East (GMM Estimation) (Lag 2)

	LogRem							
	LogRem		LogGDP	LogAid			Corr	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2	Lag1	Lag 2
Coef.	-0.4046763	-0.1539399	0.6824223	1.184464	0.0569373	0.0414704	0.1652987	0.3268409
Std. Err.	0.0496163	0.0680997	0.5609163	0.3916987	0.0485186	0.0462633	0.488027	0.3403024
z	--8.16(0.000)	-2.26(0.024)	1.22(0.224)	3.02(0.002)	1.17(0.241)	0.90(0.370)	0.34(0.735)	0.96(0.377)
95% Conf.	-0.5019225	-0.2874128	-0.4169535	0.4167486	-0.0381574	-0.0492039	-0.7912167	-0.3401396
Interval	-0.3074302	-0.0204671	1.781798	1.952179	0.1520321	0.1321447	1.121814	0.9938214

	LogGDP							
	LogRem		LogGDP	LogAid			Corr	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2	Lag1	Lag 2
Coef.	-0.0555825	0.0357467	0.3809255	0.3422233	0.110846	0.0238017	0.6255493	0.2389046
Std. Err.	0.021218	0.0388073	0.2961266	0.327446	0.082925	0.0625305	0.311301	0.257761
z	-2.62(0.009)	0.92(0.357)	1.29(0.198)	1.05(0.296)	1.34(0.181)	0.38(0.703)	2.01(0.044)	0.93(0.354)
95% Conf.	-0.097689	-0.0403142	-0.199472	-0.299559	-0.051684	-0.0987558	0.0154105	-0.2662977
Interval	-0.0139961	0.1118077	0.961323	0.9840057	0.2733761	0.1463593	1.235688	0.7441068

	LogAid							
	LogRem		LogGDP		LogAid		Corr	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2	Lag1	Lag 2
Coef.	-0.070357	0.0228656	-1.418834	-1.279295	-0.3865986	-0.3655256	-1.644666	-0.6447477
Std. Err.	0.0660664	0.1180027	0.9884934	0.930949	0.2500247	0.2047017	1.597205	1.003898
z	-1.06(0.287)	0.19(0.846)	-1.44(0.151)	-1.37(0.169)	-1.55(0.122)	- 1.79(0.074)	-1.03(0.303)	-0.64(0.521)
95% Conf.	-0.1998447	-0.2084154	-3.356246	-3.103921	-0.8766379	-0.7667335	-4.775129	-2.612352
Interval	0.0591308	0.2541466	0.5185772	0.5453318	0.1034407	0.0356823	1.485798	1.322856

	Corr							
	LogRem		LogGDP	LogAid			Corr	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2	Lag1	Lag 2
Coef.	0.0452462	0.0829955	0.5995026	-0.0194933	0.0306981	0.0319015	-0.1749299	-0.1679744
Std. Err.	0.012945	0.0251045	0.2456891	0.1531952	0.042369	0.0421517	0.3744897	0.2587618
z	3.50(0.000)	3.31(0.001)	2.44(0.015)	-0.13(0.0899)	0.72(0.469)	0.76(0.449)	-0.47(0.640)	- 0.65(0.516)
95% Conf.	0.0198744	0.0337935	0.1179608	-0.3197505	-0.0523436	-0.0507143	-0.9089163	-0.6751383
Interval	0.070618	0.1321995	1.081044	0.2807639	0.1137398	0.1145173	0.5590565	0.3391894

Table 2.7

Remittances, Aid, GDP and Corruption in the Middle East (Granger Causality Test)

Equation \ Excluded	LogRem				LogGDP				LogAid				Corr			
	LogGDP	LogAID	Corr	ALL	LogRem	LogAid	Corr	ALL	LogRem	LogGDP	Corr	ALL	LogRem	LogGDP	LogAid	ALL
chi2	10.058	1.412	1.235	16.840	34.588	2.477	5.521	78.139	3.398	4.654	1.373	18.759	12.702	8.530	0.764	29.036
Df	2	2	2	6	2	2	2	6	2	2	2	6	2	2	2	6
Prob > chi2	0.007	0.494	0.539	0.010	0.000	0.290	0.063	0.000	0.183	0.098	0.503	0.005	0.002	0.014	0.682	0.000

Table 2.8

Stationarity test: Eigenvalue stability condition; Remittances, Aid, GDP and Corruption in the Middle East

Eigenvalue		
Real	Imaginary	Modulus
0.8619063	0	0.8619063
-0.6274736	0	0.6274736
0.0209631	-0.5585333	0.5589266
0.0209631	0.5585333	0.5589266
-0.0911225	-0.5358204	0.5435134
-0.0911225	0.5358204	0.5435134
-0.3396966	0.2476475	0.4203844
-0.3396966	-0.2476475	0.4203844

All the eigenvalues lie inside the unit cercle.
pVAR satisfies stability condition.

Figure 2.4

Eigenvalue stability condition: Remittances, Aid, GDP and Corruption in the Middle East

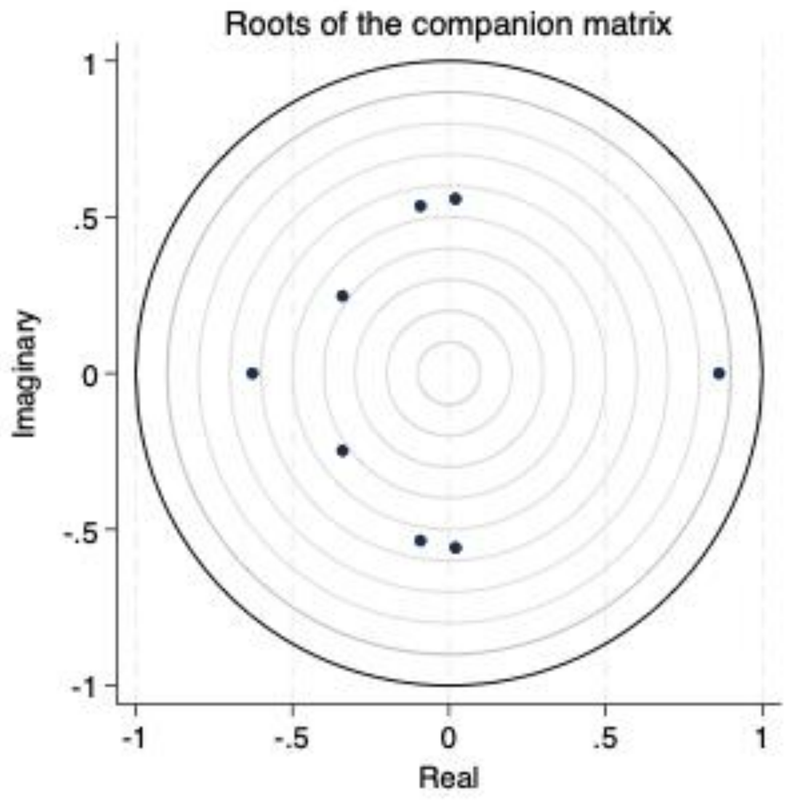


Table 2.9

Collinearity diagnostics: Remittances, Aid, GDP and Corruption in the Middle East

The Variance inflation factors (VIF) range from 1 upwards. The numerical value for VIF tells you (in decimal form) what percentage the variance is inflated for each coefficient. For example, a VIF of 1.9 tells that the variance of a particular coefficient is 90% bigger than what you would expect if there was no multicollinearity
if there was no correlation with other predictors.

A **rule of thumb** for interpreting the variance inflation factor:

- 1 = not correlated.
- Between 1 and 5 = moderately correlated.
- Greater than 5 = highly correlated.

$$VIF = \frac{1}{1 - R_i^2}$$

Nb of observations : 69

Variable	VIF	SQRT VIF	Tolerance	R-Squared
LogAid	1.05	1.02	0.9522	0.0478
logRem	1.01	1.01	0.9879	0.0121
LogGDP	1.05	1.02	0.9563	0.0437
Corr	1.01	1.01	0.9873	0.0127
Mean VIF	1.03			

	Eigenval	Cond Index
1	2.5293	1.0000
2	1.0948	1.5200
3	0.9324	1.6470
4	0.4009	2.5119
5	0.0426	7.7048
Condition Number		7.7048

Note: Eigenvalues and Cond Index computed from scaled sscp (w/ intercept)

Det(correlation matrix) 0.9421

Table 2.10

Forecast-error variance decomposition (FEVD) and Impulse Response Factor

Response variable and Forecast horizon			Impulse variable			
			LogRem	LogGDP	LogAid	Corr
	LogRem	0	0	0	0	0
		1	1	0	0	0
		2	0.8930405	0.0868541	0.0126222	0.0074831
		3	0.6519206	0.259537	0.0230115	0.0655308
		4	0.5087428	0.2447366	0.0457745	0.100746
		5	0.5881525	0.2705887	0.0454226	0.0958363
		6	0.5737638	0.2732368	0.0490017	0.1039977
		7	0.5591643	0.2844929	0.0495316	0.1068111
		8	0.5514295	0.2862067	0.0521368	0.1102271
		9	0.5456721	0.2902005	0.052888	0.1112394
		10	0.5417256	0.2918996	0.0536324	0.1127425
	LogGDP	0	0	0	0	0
		1	0.1789816	0.8210185	0	0
		2	0.1177539	0.5607127	0.0944098	0.02271235
		3	0.1511523	0.5792645	0.0816894	0.1878938
		4	0.1480622	0.5584301	0.0939282	0.1995796
		5	0.1506557	0.5656867	0.0898686	0.1937889
		6	0.1482834	0.5589566	0.0931389	0.1996211
		7	0.1495376	0.5581162	0.0934385	0.1989076
		8	0.149124	0.5559112	0.0946616	0.2003033
		9	0.1493986	0.5555703	0.0946906	0.2003405
		10	0.1492207	0.554591	0.0951685	0.2010197
	LogAid	0	0	0	0	0
		1	0.0219887	0.1631623	0.814849	0
		2	0.0256672	0.1486829	0.7142511	0.1113988
		3	0.0327059	0.1948875	0.6692364	0.1031702
		4	0.0369475	0.1997384	0.6557073	0.1076069
		5	0.0427626	0.208051	0.6395211	0.1096653
		6	0.0438584	0.2143104	0.628852	0.1129793
		7	0.0453965	0.219823	0.6197807	0.1149998
		8	0.0466828	0.2224307	0.6144341	0.1164524
		9	0.0477506	0.2248519	0.610153	0.1172446
		10	0.0482759	0.2265705	0.6071192	0.1180343
	Corr	0	0	0	0	0
		1	0.0010924	0.0008966	0.0023113	0.9956996
		2	0.079126	0.1885427	0.0131373	0.719194
		3	0.0722	0.1732954	0.0761131	0.6783915
		4	0.0752212	0.2125393	0.0738595	0.63838
		5	0.075452	0.2121778	0.0745618	0.6378084
		6	0.0781132	0.2200416	0.0768209	0.6250244
		7	0.0781966	0.2221275	0.782784	0.6213975
		8	0.0793009	0.2251709	0.0780164	0.6175117
		9	0.0795948	0.2264787	0.783632	0.6155634
		10	0.0799869	0.2280557	0.0786207	0.6133368

Figure 2.5

Impulse Response Factor (IRF)

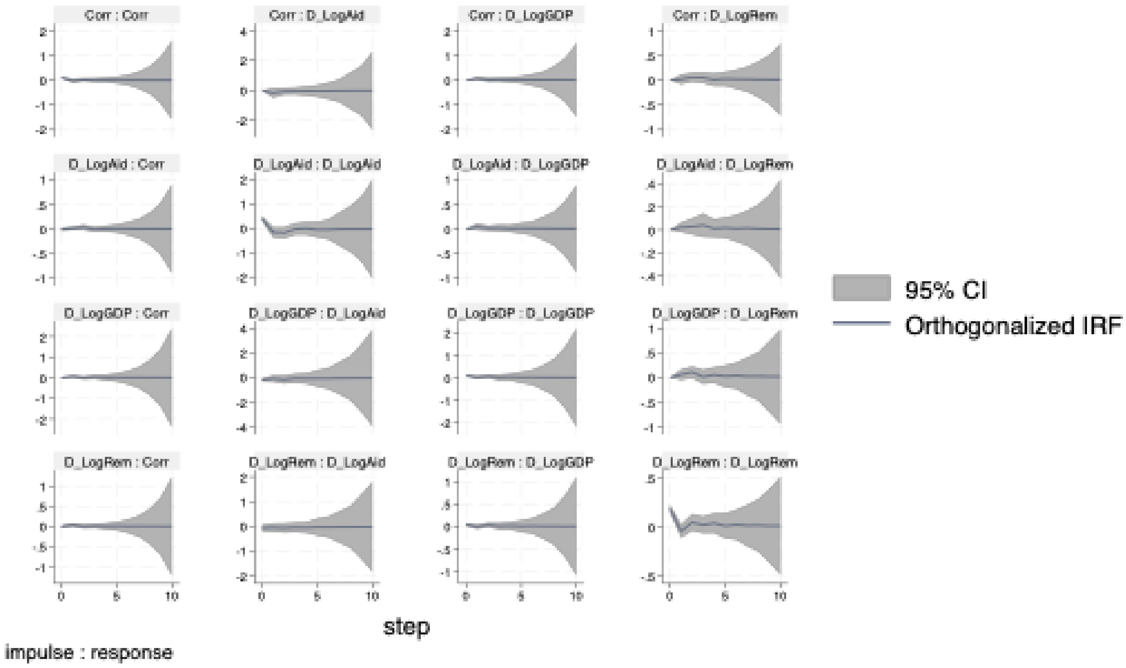


Table 2.11

Aid, GDP and Corruption in the whole model (GMM Estimation) (Lag 3)

Number Of observations: 46
Number of panels: 6
Ave. No. Of T: 7.667

	LogGDP								
	LogGDP			LogAid			Corr		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.5288083	0.2930745	0.3066848	0.765847	- 0.255019	0.22953	0.396031	-0.0981436	-0.1148813
Std. Err.	0.3342048	0.2853293	0.2924007	0.841413	0.419446	0.593075	0.200511	0.2345968	0.2127508
z	1.58(0.114)	1.03(0.304)	1.05(0.294)	0.91(0.363)	0.61 (0.543)	0.39(0.699)	0.20(0.843)	-0.42(0.676)	-0.54(0.589)
95% Conf.	-0.1262211	-0.2661607	-0.26641	-0.0883292	-0.056708	-0.932876	-0.3533912	-0.5579448	-0.5318651
Interval	1.183838	0.8523096	0.8797796	0.2414985	0.1077118	0.1391936	0.4325974	0.3616576	0.3021025

	LogAid								
	LogGDP			LogAid			Corr		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	-1.439163	-1.211418	-0.958965	-1.868895	- 0.27442	0.114336	-0.006675	0.2126279	0.6041358
Std. Err.	0.5407578	0.7163411	1.023441	0.2007002	0.197004	0.1459981	0.658853	0.9450913	1.021603
z	-2.66(0.008)	-1.69(0.091)	-0.09(0.925)	-0.93(0.352)	-1.39 (0.164)	0.78(0.434)	-0.01(0.992)	0.22(0.822)	0.59(0.554)
95% Conf.	-2.499029	-2.615421	-2.101805	-0.5802546	-0.6605407	-0.171815	-1.298003	-1.639717	-1.398168
Interval	-0.3792974	0.1925846	1.910012	0.2064756	0.1117008	0.400487	1.284653	2.064973	2.60644

	Corr								
	LogGDP			LogAid			Corr		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	-0.0332047	-0.1394927	0.0583726	-0.0020534	0.0045853	-0.513287	-0.3572244	-0.1870786	0.2510456
Std. Err.	0.1992279	0.2374458	0.2041262	-0.0471868	0.467167	0.415125	0.1113266	0.1369524	0.1513111
z	-0.17(0.868)	-0.59(0557)	0.29(0.775)	-0.04 (0.965)	0.10 (0.922)	-1.24(0.216)	-3.21(0.001)	-1.37(0.172)	1.66(0.097)
95% Conf.	-0.4236843	-0.6048779	-0.3417074	-0.0945378	-0.0869777	-0.1326917	-0.5754206	-0.4555003	-0.0455186
Interval	0.3572749	0.3258924	0.4584526	0.090431	0.0961483	0.0300343	-0.1390281	0.0813431	0.5476098

Table 2.12

Aid, GDP and Corruption in the whole model (Granger Causality Test)

Equation \ Excluded	LogGDP			LogAid			Corr		
	LogAid	Corr	ALL	LogGDP	Corr	ALL	LogGDP	Corr	ALL
chi2	1.001	3.613	9.951	11.432	1.333	14.193	0.536	2.117	2.642
Df	3	3	6	3	3	6	3	3	6
Prob > chi2	0.801	0.306	0.127	0.010	0.721	0.028	0.911	0.549	0.852

Table 2.13

Stationarity test: Eigenvalue stability condition; Aid, GDP and Corruption in the whole model

Eigenvalue		
Real	Imaginary	Modulus
0.9143528	0	0.9143528
-0.1870092	0.683188	0.7083208
-0.1870092	-0.683188	0.7083208
-0.4471842	0.5194569	0.6854263
-0.4471842	-0.5194569	0.6854263
-0.307446	0.5240673	0.6075932
-0.307446	-0.5240673	0.6075932
0.4768101	-0.1498847	0.4998133
0.4768101	0.1498847	0.4998133

All the eigenvalues lie inside the unit cercle.
pVAR satisfies stability condition.

Figure 2.6

Eigenvalue stability condition: Aid, GDP and Corruption in the whole model

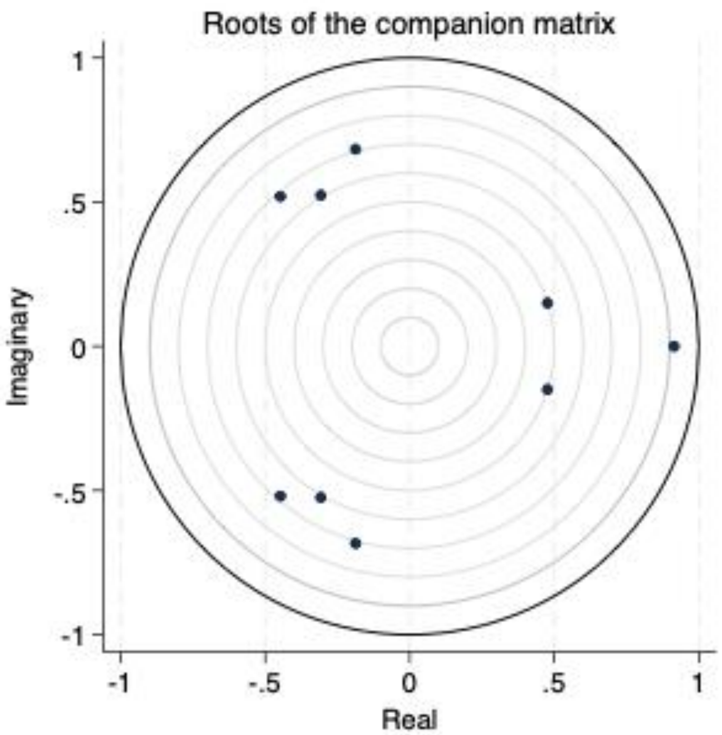


Table 2.14

Collinearity diagnostics: Aid, GDP and Corruption in the whole model

The Variance inflation factors (VIF) range from 1 upwards. The numerical value for VIF tells you (in decimal form) what percentage the variance is inflated for each coefficient. For example, a VIF of 1.9 tells that the variance of a particular coefficient is 90% bigger than what you would expect if there was no multicollinearity
if there was no correlation with other predictors.

A **rule of thumb** for interpreting the variance inflation factor:

- 1 = not correlated.
- Between 1 and 5 = moderately correlated.
- Greater than 5 = highly correlated.

$$VIF = \frac{1}{1 - R_i^2}$$

Nb of observations : 70

Variable	VIF	SQRT VIF	Tolerance	R-Squared
LogGDP	1.01	1.01	0.9857	0.0143
logAid	1.01	1.01	0.9880	0.0120
Corr	1.01	1.00	0.9948	0.0052
Mean VIF	1.01			

	Eigenval	Cond Index
1	1.6903	1.0000
2	1.0216	1.2863
3	0.9699	1.3201
4	0.3182	2.3049
Condition Number		2.3049

Note: Eigenvalues and Cond Index computed from scaled sscp (w/ intercept)

Det(correlation matrix) 0.9845

Table 2.15

Optimal lag in our PVAR model: Aid, GDP and Corruption in the whole model

Number Of observations: 40
Number of panels: 5
Ave. No. Of T: 8.000

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.7741873	25.23154	0.5614878	-74.36821	-28.76846	-45.25589
2	0.8883521	16.66942	0.5459327	-49.73041	-19.33058	-30.3222
3	0.6351654	5.703712	0.7691667	-27.4962	-12.29629	-17.7921

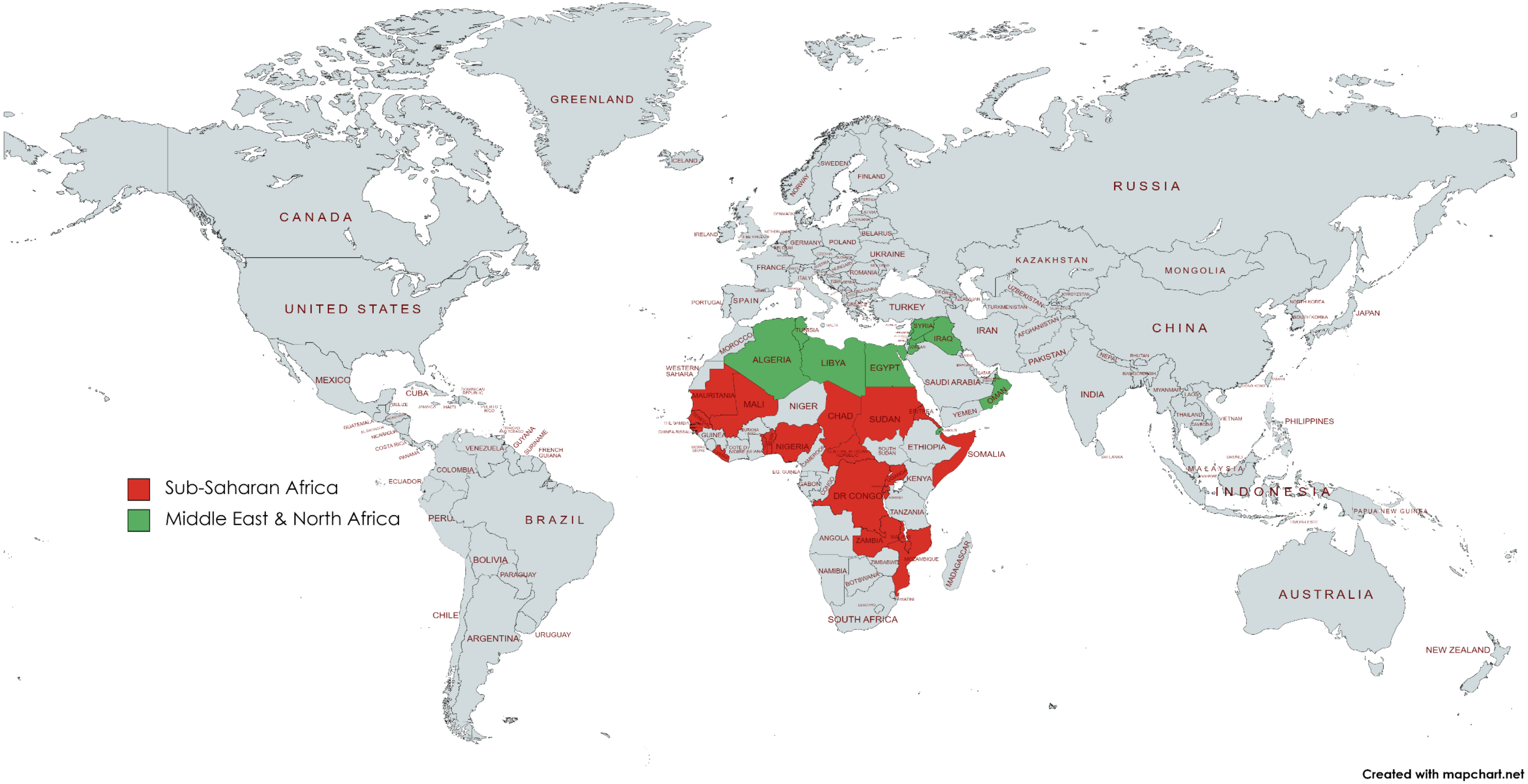
Table 2.16

List of sample countries

1 - Algeria	11 - Guinea-Bissau	21 - Nigeria	31 - West Bank and Gaza
2 - Benin	12 - Iraq	22 - Oman	32 - Zambia
3 - Burundi	13 - Jordan	23 - Rwanda	
4 - Central African Republic	14 - Lebanon	24 - Senegal	
5 - Chad	15 - Liberia	25 - Somalia	
6 - Congo. Dem. Rep.	16 - Libya	26 - Sudan	
7 - Djibouti	17 - Malawi	27 - Syrian Arab Republic	
8 - Egypt. Arab Rep.	18 - Mali	28 - Togo	
9 - Eritrea	19 - Mauritania	29 - Tunisia	
10 - Gambia. The	20 - Mozambique	30 - Uganda	

Figure 2.7

Cartography of sample countries



3. Annexe chapitre 3

Tables of correlation and causality

Table 3.1
Correlation and causality in MENA Region and Sub-Saharan Africa (Lag 1)

	LogInformal		
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.8453803	0.0601146	-0.1124868
Std. Err.	0.053754	0.0243894	0.0629
z	15.78***(0.000)	2.46*(0.014)	-1.79 (0.074)
95% Conf.	0.7403744	0.123123	-0.2357685
Interval	0.9503861	0.107917	0.107949

	LogRem		
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.338493	0.9679429	0.0366235
Std. Err.	0.1811349	0.924027	0.1697083
z	0.19(0.852)	10.48***(0.000)	0.22(0.829)
95% Conf.	-0.3211687	0.786837	0.2959987
Interval	0.3888672	1.149049	0.3692457

	PS		
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.0535468	-0.0366996	0.9963843
Std. Err.	0.0873081	0.0346203	0.0752386
z	0.61(0.540)	-1.06(0.289)	13.24***(0.000)
95% Conf.	-0.1175739	-0.1045541	0.8489193
Interval	0.2246675	0.0311548	1.143849

Granger test:

Equation \ Excluded	LogInformal			LogRem			PS		
	LogRem	ps	ALL	LogInformal	ps	ALL	LogInformal	LogRem	ALL
chi2	6.075	3.198	6.140	0.035	0.047	0.047	0.376	1.124	2.317
df	1	1	2	1	1	2	1	1	2
Prob > chi2	0.014	0.074	0.046	0.852	0.829	0.977	0.540	0.289	0.314

Panel VAR (p-VAR)

- **GMM Estimation:** This indicates that the model was estimated using the Generalized Method of Moments (GMM), a technique commonly used in panel data analysis to address potential endogeneity and correlation issues.

- **LogInformal, LogRem, ps:** These are the variables included in the p-VAR model. The "L1." in front of them means they are lagged by one period.

- **Coefficients and Standard Errors:** The coefficients show the estimated relationships between the variables. For example, a one-unit increase in lagged LogInformal is associated with an 0.845 increase in current LogInformal. The standard errors measure the uncertainty around these estimates.

- **z and P>z:** These are the z-statistics and p-values for the coefficients. They test whether the coefficients are statistically significant (i.e., different from zero). In this case, most lagged coefficients are significant, indicating that the variables are likely to influence each other over time.

Granger Causality Tests

- **Ho and Ha:** The null hypothesis (Ho) is that the excluded variable does not Granger-cause the equation variable. The alternative hypothesis (Ha) is that it does.

- **chi2, df, Prob > chi2:** These are the chi-squared statistic, degrees of freedom, and p-value for the Granger causality test. The p-value indicates the probability of observing a test statistic as extreme as or more extreme than the one calculated, assuming the null hypothesis is true.

Interpretation of Granger Causality Results

- **LogRem Granger-causes LogInformal:** The p-value (0.014) is less than the conventional significance level of 0.05, so we reject the null hypothesis and conclude that LogRem Granger-causes LogInformal. This means that past values of LogRem help predict current values of LogInformal.

- **ps Granger-causes LogInformal:** The p-value (0.074) is slightly above 0.05, so we fail to reject the null hypothesis at the 5% level. However, it is close to being significant, suggesting a potential weak Granger causal relationship.

- **No other significant Granger causal relationships:** The other p-values are all above 0.05, so we fail to reject the null hypothesis for these pairs of variables.

Number Of observations: 385
Number of panels: 22
Ave. No. Of T: 17.500

Table 3.2
Correlation and causality in MENA Region and Sub-Saharan Africa (Lag 2)

	LogInformal					
	LogInformal		LogRem		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.7396507	0.0944383	0.736987	-0.127218	-0.1156011	0.0011914
Std. Err.	0.1518668	0.1356557	0.0302511	0.0148645	0.0651644	0.0353576
z	4.87***(0.000)	0.70(0.486)	2.44**(0.015)	-0.86(0.392)	-1.77(0.076)	0.03(0.973)
95% Conf.	0.4419072	-0.1714419	0.0144077	-0.0418556	-2.43321	-0.0681083
Interval	1.037214	0.3603185	0.1329898	0.0164121	0.0121188	0.0704911

	LogRem					
	LogInformal		LogRem		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.326672	-0.2203865	0.9503132	-0.0204795	-0.219315	0.1270841
Std. Err.	0.3448019	0.2667508	0.1149867	0.1003069	0.2238874	0.1931651
z	0.95(0.343)	-0.83(0.409)	8.26***(0.000)	-0.21(0.837)	-0.10(0.922)	0.66(0.511)
95% Conf.	-0.3491273	-0.7432085	0.7249435	-0.2171773	-0.4607427	-0.2515126
Interval	1.002471	0.3024355	1.175683	0.1760183	0.4168798	0.5056809

	PS					
	LogInformal		LogRem		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.644087	-0.036196	-0.0326188	0.0079643	0.9969981	-0.0472671
Std. Err.	0.1181979	0.0864544	0.0386419	0.0256022	0.1012987	0.888518
z	0.54(0.586)	-0.42(0.675)	-0.84(0.399)	0.31(0.756)	9.84***(0.000)	-0.53(0.595)
95% Conf.	-0.167255	-0.2056436	-0.1083555	-0.0422151	0.7984564	-0.2214133
Interval	0.2960724	0.1332516	0.0431179	0.0581437	1.19554	0.1268792

Granger test:

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInformal	ps	ALL	LogInformal	LogRem	ALL
chi2	6.068	3.164	6.247	0.912	0.579	1.493	0.305	0.713	2.079
df	2	2	4	2	2	4	2	2	4
Prob > chi2	0.048	0.206	0.181	0.634	0.749	0.828	0.859	0.700	0.721

Table 3.3

Correlation and causality in MENA Region and Sub-Saharan Africa (Lag 3)

Number Of observations: 362
Number of panels: 22
Ave. No. Of T: 16.455

	LogInformal								
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.7951596	0.1694154	-0.1180774	0.0594186	-0.0080147	-0.0022929	-0.1038448	-0.0019902	0.0038996
Std. Err.	0.1558166	0.1555772	-0054191	0.0282964	0.0187167	0.0105527	0.0693117	0.0409488	0.036066
z	5.10***(0.000)	1.09(0.276)	-2.18(0.029)	2.10*(0.036)	-0.43(0.668)	-0.22(0.828)	-1.50(0.134)	-0.05(0.961)	0.11(0.914)
95% Conf.	0.4897646	-0.1355102	-0.2242899	0.0039587	-0.0446988	-0.229758	-0.2396933	-0.0822485	0.0667884
Interval	1.100555	0.4743411	-0.0118649	0.1148785	0.0286694	0.0183901	0.0320036	0.078268	0.0745876
	LogRem								
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.3866773	-1.1797432	-0.0789417	0.938758	0.0348156	-0.610517	-0.0185637	0.1480924	-0.0271387
Std. Err.	0.3575031	0.2853772	0.1888534	0.119741	0.1289606	0.0840281	0.2455316	0.2436163	0.1584798
z	1.08(0.279)	-0.63(0.529)	-0.42(0.676)	7.84***(0.000)	0.27(0.787)	-0.73(0.467)	-0.08(0.940)	0.61(0.543)	-0.17(0.864)
95% Conf.	-0.3140159	-0.7390722	-0.4490876	0.7040699	-0.2179425	-0.2257437	-0.4997967	-0.3293868	-0.3377533
Interval	1.08737	0.3795859	0.0745876	1.173446	0.2875737	0.1036403	0.4626693	0.6255717	0.283476
	PS								
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.0875825	-0.0010517	-0.0478968	-0.0399565	0.0178049	-0.007493	0.9594889	-0.068963	0.053058
Std. Err.	0.1213867	0.1109015	0.0872313	0.403466	0.027942	0.0251451	0.106301	0.0841605	0.0482764
z	0.72(0.471)	-1.01(0.992)	-0.55(0.583)	-0.99(0.322)	0.64(0.524)	-0.30(0.766)	9.03***(0.000)	-0.82(0.413)	1.10(0.272)
95% Conf.	-0.1503312	-0.2184146	-0.2188671	-0.1190344	-0.0369604	-0.0567798	0.7511428	-0.2339146	-0.0415619
Interval	0.3254961	0.2163111	0.1230735	0.0391215	0.0725703	0.0417872	1.167835	0.0959886	0.14678

Granger test:

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInformal	ps	ALL	LogInformal	LogRem	ALL
chi2	4.588	2.636	4.837	1.220	0.594	2.041	0.749	1.153	3.128
df	3	3	6	3	3	6	3	3	6
Prob > chi2	0.205	0.451	0.565	0.748	0.898	0.916	0.862	0.764	0.793

Number Of observations: 399
Number of panels: 21
Ave. No. Of T: 19.000

Table 3.4

Correlation and causality in Latin America Region (Lag 1)

	LogInformal		
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.8392321	0.1006696	-0.0185053
Std. Err.	0.0622309	0.0439035	0.0395146
z	13.49***(0.000)	2.29*(0.022)	-0.47(0.640)
95% Conf.	0.7172618	0.0146203	-0.0959525
Interval	0.9612024	0.1867189	0.058942

	LogRem		
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.8546292	0.282111	0.641814
Std. Err.	0.2416439	0.1731138	0.1671121
z	3.54***(0.000)	1.63(0.103)	0.38(0.701)
95% Conf.	0.3810335	-0.0571858	-0.2633522
Interval	1.328225	0.6214077	0.391715

	ps		
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.0607033	-0.0054925	0.8505773
Std. Err.	0.0882709	0.053449	0.1102841
z	0.69(0.492)	-0.10(0.918)	7.71***(0.000)
95% Conf.	-0.1123046	-0.1102507	0.6344244
Interval	0.2337111	0.992657	1.06673

Granger test:

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInformal	ps	ALL	LogInforml	LogRem	ALL
chi2	5.258	0.219	6.364	12.509	0.148	15.432	0.473	0.011	2.827
df	1	1	2	1	1	2	1	1	2
Prob > chi2	0.022	0.640	0.042	0.000	0.701	0.000	0.492	0.918	0.243

Number Of observations: 376
Number of panels: 21
Ave. No. Of T: 17.905

Table 3.5

Correlation and causality in Latin America Region (Lag 2)

	LogInformal					
	LogInformal		LogRem		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.5189676	-0.0020748	0.3389896	0.0234207	0.0089076	-0.0864376
Std. Err.	0.4199867	0.1215327	0.2324969	0.0195498	0.0555605	0.0603564
z	1.24(0.217)	-0.02(0.986)	1.46(0.145)	1.20(0.231)	0.16(0.873)	-1.43(0.152)
95% Conf.	-0.3041912	-0.2402744	-0.1166959	-0.0148962	-0.99989	-0.204734
Interval	1.342126	0.2361249	0.794675	0.0617376	0.1178041	0.0318588

	LogRem					
	LogInformal		LogRem		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.2495699	0.0402886	0.7392583	-0.0415592	-0.0612996	0.0410912
Std. Err.	0.7517265	0.1548751	0.5107101	0.196723	0.0741749	0.053868
z	0.33(0.740)	0.26(0.759)	1.45(0.148)	-2.11(0.035)	-0.83(0.409)	0.76(0.446)
95% Conf.	-1.223787	-0.263261	-0.2617151	-0.0801162	-0.2066797	-0.064488
Interval	1.722927	0.3438383	1.740232	-0.0030023	0.0840804	0.1466705

	PS					
	LogInformal		LogRem		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	-0.0596969	0.0188725	0.0451681	0.0301917	0.827837	0.0920784
Std. Err.	0.530627	0.1564046	0.3119626	0.0209521	0.1063846	0.1152653
z	-0.115(0.910)	0.12(0.904)	0.14(0.885)	1.44(0.150)	7.78***(0.000)	0.80(0.424)
95% Conf.	-1.099707	-0.2876749	-0.5662673	-0.0108736	0.6193036	-0.1338374
Interval	0.980313	0.3254199	0.6566035	0.071257	1.036324	0.3179942

Granger test:

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInforml	ps	ALL	LogInformal	LogRem	ALL
chi2	2.542	0.086	4.520	0.546	1.061	1.264	0.015	2.253	8.753
df	2	2	4	2	2	4	2	2	4
Prob > chi2	0.281	0.352	0.340	0.761	0.588	0.867	0.992	0.324	0.068

Table 3.6

Correlation and causality in Latin America Region (Lag 3)

Number Of observations: 354
Number of panels: 21
Ave. No. Of T: 16.857

	LogInformal								
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.1713452	0.1768504	-0.0269669	0.4086816	0.0943397	0.0299244	-0.0350999	0.0203511	-0.119838
Std. Err.	1.093487	0.3322144	0.0831168	0.4369983	0.1635226	0.0540839	0.0863595	0.1141009	0.1226621
z	0.16(0.875)	0.53(0.594)	-0.32(0.746)	0.94(0.350)	0.58(0.564)	0.55(0.580)	-0.41(0.684)	0.18(0.858)	-0.98(0.329)
95% Conf.	-1.97185	-0.4742779	-0.1898728	-0.4478193	-0.2261587	-0.076078	-0.2043614	-0.2032826	-0.3602513
Interval	2.31454	0.8279787	0.135939	1.265183	0.4148382	0.1359268	0.1341616	0.2439848	0.1205753
	LogRem								
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.826089	-0.1128749	-0.0627139	0.607746	-0.1520875	-0.0472742	-0.25463	-0.0767457	0.1265292
Std. Err.	1.786664	0.4683733	0.1362355	0.7961304	0.2089404	0.0850593	0.1047115	0.1814431	0.233297
z	0.46(0.644)	-0.24(0.810)	-0.46(0.645)	0.79(0.429)	-0.73(0.467)	-0.56(0.578)	-0.24(0.808)	-0.42(0.672)	0.54(0.588)
95% Conf.	-2.675587	-1.03087	-0.3291306	-0.8997632	-0.5616032	-0.2139873	-0.2306937	-0.4323677	-0.3307245
Interval	4.328005	0.80512	0.2043028	2.115172	0.2574282	0.1194389	0.1797676	0.2788763	0.5837829
	PS								
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	-0.5138577	0.1999311	-0.048549	0.1309883	0.1790267	0.0278241	0.7512232	0.164115	-0.0116789
Std. Err.	1.19056	0.3212893	0.1235548	0.4813578	0.1592799	0.0623832	0.1129051	0.1534169	0.120615
z	-0.43(0.666)	0.62(0.534)	-0.39(0.694)	0.27(0.786)	1.12(0.261)	0.45(0.656)	6.65***(0.000)	1.07(0.285)	-0.10(0.923)
95% Conf.	-2.847313	-04297843	-0.2907119	-0.8124558	-0.1331563	-0.0944447	0.5299332	-0.1365766	-0.24808801
Interval	1.819597	0.8296465	0.1936139	1.074432	0.4912096	0.1500929	0.9725132	0.4648065	0.2247222

Granger test:

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInforml	ps	ALL	LogInforml	LogRem	ALL
chi2	1.259	1.736	2.093	0.413	0.613	0.724	0.544	2.635	11.126
df	3	3	6	3	3	6	3	3	6
Prob > chi2	0.739	0.629	0.911	0.938	0.894	0.994	0.909	0.451	0.085

Table 3.7
Correlation and causality in OECD Countries (Lag 1)

Number Of observations: 565
Number of panels: 38
Ave. No. Of T: 14.868

	LogInformal		
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.8953818	0.0692069	0.0486066
Std. Err.	0.0257093	0.0203035	0.0593826
z	34.83***(0.000)	3.41**(0.001)	0.82(0.413)
95% Conf.	0.8449925	0.0294128	-0.0677811
Interval	0.9457711	0.109001	0.1649944

	LogRem		
	LogInformal	LogRem	ps
	Lag1	Lag1	Lag1
Coef.	-0.0462552	0.9196654	0.1940397
Std. Err.	0.0698064	0.07842264	0.1179327
z	-0.66(0.508)	11.73***(0.000)	1.65(0.100)
95% Conf.	-0.1830733	0.7659525	-0.0371042
Interval	0.0905629	1.073378	0.4251835

	ps		
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.0389493	-0.0470712	0.8327858
Std. Err.	0.0521309	0.0465519	0.1037744
z	0.75(0.455)	-1.01(0.312)	8.02***(0.000)
95% Conf.	-0.0622254	-1.383113	0.6293918
Interval	0.1411241	0.0441689	1.03618

Granger test :

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInforml	ps	ALL	LogInforml	LogRem	ALL
chi2	11.619	0.670	12.873	0.439	2.707	3.266	0.588	1.022	1.051
df	1	1	2	1	1	2	1	1	2
Prob > chi2	0.001	0.413	0.002	0.508	0.100	0.195	0.455	0.312	0.591

Table 3.8
Correlation and causality in OECD Countries (Lag 2)

Number Of observations: 526
Number of panels: 38
Ave. No. Of T: 13.842

	LogInformal					
	LogInformal		LogRem		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	1.167744	-0.2832315	0.0457344	0.03476	0.1100709	-0.0018152
Std. Err.	0.0641595	0.0501351	0.351472	0.160856	0.0550295	0.0296677
z	18.20***(0.000)	-5.65***(0.000)	1.30(0.193)	2.13*(0.033)	2.00*(0.045)	-0.06(0.951)
95% Conf.	1.041993	-0.3814946	-0.0231528	0.0027488	0.0022151	-0.0599627
Interval	1.293494	-0.1849685	0.1146215	0.0658033	0.2179268	0.0563324

	LogRem					
	LogInformal		LogRem		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	-0.0383938	0.0443598	0.909262	-0.01065172	0.1656521	-0.1128504
Std. Err.	0.1329821	0.1145663	0.1224874	0.0506786	0.1003116	0.0618005
z	-0.29(0.773)	0.39(0.699)	7.42***(0.000)	-2.10 (0.036)	1.65*(0.099)	-1.83*(0.068)
95% Conf.	-0.200034	-0.180186	0.669191	-0.2058454	-0.0309549	-0.2339773
Interval	0.2222463	0.2689055	1.149333	-0.0071889	0.3622591	0.0082764

	PS					
	LogInformal		LogRem		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	-0.3016356	0.2791754	-.0.1445049	0.1021394	0.9312334	-0.1523752
Std. Err.	0.1125404	0.885264	0.0751706	0.0353762	0.0978688	0.0580343
z	-2.68**(0.007)	3.15**(0.002)	-1.92*(0.055)	2.89**(0.004)	9.52***(0.000)	-2.63**(0.009)
95% Conf.	-0.5222109	0.1056669	-0.2918365	0.0328034	0.739414	-0.2661204
Interval	-0.0810604	0.4526839	0.0028266	0.1714754	1.123053	-0.03863

Granger test :

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInformal	ps	ALL	LogInformal	LogRem	ALL
chi2	17.474	4.815	22.016	0.159	6.617	7.258	9.965	8.405	22.502
df	2	2	4	2	2	4	2	2	4
Prob > chi2	0.000	0.090	0.000	0.924	0.037	0.123	0.007	0.015	0.000

Table 3.9

Correlation and causality in OECD Countries (Lag 3)

Number Of observations: 487
Number of panels: 38
Ave. No. Of T: 12.816

	LogInformal								
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	1.136251	-0.2982462	0.0247549	0.115877	-0.0099529	0.0240281	0.1351462	-0.0285333	0.0464022
Std. Err.	0.0697511	0.072963	0.0470291	0.0582035	0.0221935	0.0177107	0.709566	0.0315618	0.0424375
z	16.29***(0.000)	-4.09***(0.000)	0.53(0.599)	1.99*(0.046)	-0.45(0.654)	1.36(0.175)	1.90*(0.057)	-0.90(0.366)	1.09(0.274)
95% Conf.	0.9995607	-0.4412511	-0.0674204	0.0018002	-0.0534514	-.0106843	-0.0039262	-0.0903933	-0.0367737
Interval	1.272941	-0.1552412	0.1169302	0.2299538	0.0335456	0.0587405	0.2742186	0.0333267	0.1295781
	LogRem								
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.0527431	-0.158474	0.0793508	0.8967679	-0.0711191	-0.0257777	0.0441247	-0.1040292	-0.0215873
Std. Err.	0.1287574	0.1558165	0.1003682	0.11663246	0.0547125	0.0427281	0.1012991	0.0547334	0.0645955
z	0.41(0.682)	-1.02(0.309)	0.79(0.429)	7.69***(0.000)	-1.30(0.194)	-0.60(0.546)	0.44(0.663)	-1.90*(0.057)	-0.33(0.738)
95% Conf.	-0.1996168	-0.4638687	-0.1173673	0.6681683	-0.1783537	-0.1095232	-0.1544179	-0.2113047	-0.1481922
Interval	0.305103	0.1469208	0.276088	1.125368	0.0361155	0.0579678	0.2426672	0.0032464	0.1050176
	PS								
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	-0.2697594	0.3540739	-0.0640324	-0.2214773	0.1349376	-0.116693	0.9211429	-0.1847498	0.0821311
Std. Err.	0.1192152	0.1223949	0.0908496	0.1153001	0.0521231	0.0469624	0.1240155	0.0687993	0.0720053
z	-2.26*(0.024)	2.89**(0.004)	-0.70(0.481)	-1.92*(0.055)	2.59*(0.010)	-0.25(0.804)	7.43***(0.000)	-2.69**(0.007)	1.14(0.254)
95% Conf.	-0.503417	0.1141843	-0.2420943	-0.4474614	0.0327782	-0.103714	0.6780769	-0.3195939	-0.0589967
Interval	-0.0361019	0.5939635	0.1140295	0.0045068	0.237097	0.0803754	1.164209	-0.0499056	0.2232589

Granger test :

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInformal	ps	ALL	LogInformal	LogRem	ALL
chi2	22.744	4.098	28.767	1.248	5.601	6.383	11.732	11.470	26.537
df	3	3	6	3	3	6	3	3	6
Prob > chi2	0.000	0.251	0.000	0.742	0.133	0.382	0.008	0.009	0.000

Table 3.10

Correlation and causality in OECD Countries (Lag 1): remittances paid

Number Of observations: 732
Number of panels: 38
Ave. No. Of T: 19.263

	LogInformal		
	LogInformal	LogRemPaid	PS
	Lag1	Lag1	Lag1
Coef.	0.9580286	-0.0059135	0.0007373
Std. Err.	0.0567127	0.0174086	0.0341418
z	16.89***(0.000)	-0.34(0.743)	0.02(0.983)
95% Conf.	0.8468737	-0.0400338	-0.0661794
Interval	1.069183	0.0282068	0.067654

	LogRemPaid		
	LogInformal	LogRemPaid	PS
	Lag1	Lag1	Lag1
Coef.	0.2069279	0.8769278	-0.1369653
Std. Err.	0.2321372	0.0908481	0.140922
z	0.89(0.373)	9.65***(0.000)	-0.97(0.331)
95% Conf.	-2.2480525	0.6988689	-0.4131672
Interval	0.6619084	1.054987	0.1392367

	PS		
	LogInformal	LogRemPaid	PS
	Lag1	Lag1	Lag1
Coef.	0.0795029	-0.154484	0.9874803
Std. Err.	0.1489162	0.441194	0.0736594
z	0.53(0.593)	-0.35(0.726)	13.41***(0.000)
95% Conf.	-0.2123675	-0.1019208	0.8431105
Interval	0.3713732	0.071024	1.13185

Granger test:

Equation \ Excluded	LogInformal			LogRemPaid			PS		
	LogRemPaid	PS	ALL	LogInformal	PS	ALL	LogInformal	LogRemPaid	ALL
chi2	0.115	0.000	0.117	0.795	0.945	1.568	0.285	0.123	0.574
df	1	1	2	1	1	2	1	1	2
Prob > chi2	0.734	0.983	0.943	0.373	0.331	0.456	0.593	0.726	0.750

Table 3.11

Number Of observations: 693
Number of panels: 38
Ave. No. Of T: 18.23

Correlation and causality in OECD Countries (Lag 2): remittances paid

	LogInformal					
	LogInformal		LogRemPaid		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	1.360466	-0.3840207	-0.0065308	0.002945	0.0583471	-0.0193248
Std. Err.	0.073654	0.0481134	0.160094	0.114866	0.036415	0.0229302
z	18.47***(0.000)	-7.98***(0.000)	-0.41(0.683)	0.26(0.798)	1.60(0.109)	-0.84(0.399)
95% Conf.	1.216107	-0.4783212	-0.0379087	-0.195684	-0.013025	-0.0642671
Interval	1.504825	-2.2897202	0.248471	0.0254584	0.1297192	0.0256175

	LogRemPaid					
	LogInformal		LogRemPaid		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.9924805	-0.6764348	0.9617891	-0.0874437	-1.1046627	0.0476408
Std. Err.	0.3131534	0.2367045	0.0845231	0.0368543	0.1426004	0.1299767
z	3.17**(0.002)	-2.86**(0.004)	11.83***(0.000)	-2.37*(0.018)	-0.73(0.463)	0.37(0.714)
95% Conf.	0.378112	-1.140367	0.7961268	-0.1596767	-0.3841544	-0.2071088
Interval	1.60625	- 0.2125025	1.127451	- 0.0152107	0.174829	0.3023905

	PS					
	LogInformal		LogRemPaid		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	-0.3035668	0.3629499	0.0068936	-0.0327596	1.021767	-0.0914943
Std. Err.	0.14883	0.1026519	0.0389419	0.204105	0.0814005	0.0557938
z	- 2.04*(0.041)	0.354***(0.000)	0.18(0.859)	-1.61(0.108)	12.55***(0.000)	-1.64(0.101)
95% Conf.	-5.5952683	0.1617559	-0.064311	-0.0727635	0.862225	-0.2008482
Interval	-0.118654	0.5641439	0.832182	0.0072444	1.181309	0.0178596

Granger test:

Equation \ Excluded	LogInformal			LogRemPaid			PS		
	LogRemPaid	PS	ALL	LogInformal	PS	ALL	LogInformal	LogRemPaid	ALL
chi2	0.197	2.897	2.982	11.410	0.557	12.668	13.365	2.723	14.591
df	2	2	4	2	2	4	2	2	4
Prob > chi2	0.906	0.235	0.561	0.003	0.757	0.013	0.001	0.256	0.006

Table 3.12

Number Of observations: 655
Number of panels: 38
Ave. No. Of T: 17.237

Correlation and causality in OECD Countries (Lag 3): remittances paid

	LogInformal								
	LogInformal			LogRemPaid			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	1.325388	-0.3951468	0.0058838	0.0013966	0.0042726	0.0015986	0.0483507	-0.0127384	0.0005039
Std. Err.	0.0757871	0.0697635	0.0472766	0.0156652	0.0122517	0.0080384	0.382625	0.0228755	0.0225063
z	17.49***(0.000)	-5.66***(0.000)	0.12(0.901)	0.09(0.929)	0.35(0.727)	0.20(0.842)	1.26(0.206)	-0.56(0.578)	0.02(0.982)
95% Conf.	1.176848	0.5318808	-0.0867765	-0.0293066	-0.197402	-0.014564	-0.0266424	-0.0575737	-0.0436077
Interval	1.473928	-0.2584128	0.0985442	0.0320998	0.0282855	0.0173536	0.1233438	0.0320968	0.0446155
	LogRemPaid								
	LogInformal			LogRemPaid			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	1.04929	-0.4397908	-0.2387666	0.9472194	-1.176453	0.0943482	-0.0279132	-0.123861	0.1550785
Std. Err.	0.3389495	0.2950484	0.2144998	0.902345	0.1095718	0.1199293	0.1479484	0.1368853	0.121102
z	3.10**(0.002)	-1.49(0.136)	-1.11(0.266)	10.50***(0.000)	-1.61(0.107)	0.79(0.431)	-0.19(0.850)	-0.90(0.366)	1.28(0.200)
95% Conf.	0.3849615	-1.018075	-0.6591785	0.7703614	-0.3912098	-0.1407088	-0.3178867	-0.3921513	-0.082277
Interval	1.713619	0.1384933	1.1816454	1.124078	0.0383039	0.3294052	0.2620603	0.1444293	0.392434
	PS								
	LogInformal			LogRemPaid			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	-0.2925123	0.3831569	0.0161488	-0.0023633	-0.0225452	-0.0162553	1.013667	-0.1938092	0.1450766
Std. Err.	0.1603349	0.1320686	0.1144485	-0.0404404	0.0288827	0.0265107	0.0856549	0.0643041	0.0571436
z	-1.82*(0.068)	2.90**(0.004)	0.14(0.888)	-0.06(0.953)	-0.78(0.435)	-0.61(0.540)	11.83***(0.000)	-3.01**(0.003)	2.54*(0.011)
95% Conf.	-0.6067629	0.1243072	-0.2081662	-0.0816249	-0.0791542	-0.682154	0.8457862	-0.3198428	0.330771
Interval	0.0217383	0.6420065	0.2404638	0.0768984	0.0340638	0.0357048	1.181547	-0.0677755	0.257076

Granger test:

Equation \ Excluded	LogRem			LogInformal			PS		
	LogInformal	PS	ALL	LogRem	PS	ALL	LogRem	LogInformal	ALL
chi2	0.258	2.032	2.336	11.886	2.078	14.651	14.092	2.539	15.453
df	3	3	6	3	3	6	3	3	6
Prob > chi2	0.968	0.566	0.886	0.008	0.556	0.023	0.003	0.468	0.017

Table 3.13

Correlation and causality in OECD Countries (Lag 4): remittances paid

Number Of observations: 617
Number of panels: 37
Ave. No. Of T: 16.676

	LogInformal											
	LogInformal				LogRemPaid				PS			
	Lag1	Lag2	Lag3	Lag4	Lag1	Lag2	Lag3	Lag4	Lag1	Lag2	Lag3	Lag4
Coef.	1.372205	-0.5160073	0.2440756	-0.1604935	-0.004512	0.004867	0.0068582	-0.0075928	0.0301961	-0.0100302	0.0278012	-0.045057
Std. Err.	0.73417	0.0659754	0.0655038	0.471395	0.0159081	0.0129691	0.0087171	0.0079789	0.0406977	0.0226054	0.0248027	0.0198689
z	18.70***(0.000)	-7.82***(0.000)	3.73***(0.000)	3.40**(0.001)	-0.28(0.777)	0.38(0.707)	0.79(0.341)	-0.95(0.341)	0.74(0.458)	-0.44(0.657)	1.12(0.262)	-2.27*(0.023)
95% Conf.	1.22931	-0.6453166	0.1156905	-0.2528852	-0.0356913	-0.0205518	-0.0102271	-0.0232311	-0.04957	-0.0543359	-0.0208112	-0.839994
Interval	1.517099	-0.3866979	0.3724608	-0.681017	0.0266672	0.0302859	0.0239435	0.0080455	0.1099622	0.0342755	0.0764135	-0.0061146
	LogRemPaid											
	LogInformal				LogRemPaid				PS			
	Lag1	Lag2	Lag3	Lag4	Lag1	Lag2	Lag3	Lag4	Lag1	Lag2	Lag3	Lag4
Coef.	1.48823	-0.8511229	0.2273042	-0.2028999	0.8844218	-0.1827917	0.1597261	-0.0903786	-0.0658525	-0.1000252	0.0426899	0.00841745
Std. Err.	0.3457734	0.2954237	0.3110301	0.2347202	0.0967798	0.1079157	0.124241	0.0547876	0.1571627	0.1378448	0.1014052	0.1404585
z	4.30***(0.000)	-2.88**(0.004)	0.73(0.465)	-0.86(0.387)	9.14***(0.000)	-1.69*(0.90)	1.29*(1.99)	-1.65*(0.099)	-0.42(0.675)	-0.73(0.468)	0.42(0.674)	0.60(0.549)
95% Conf.	0.8105262	-1.430143	-0.3823036	-0.66243	0.6947369	-0.3943026	-0.0837818	-0.1977602	-0.3738857	-0.3701961	-0.1560606	-0.1911191
Interval	2.165933	-0.2721031	0.8369119	0.2571431	1.074107	0.0287192	0.4032341	0.0170031	0.2421807	0.1701456	0.2414404	0.3594682
	PS											
	LogInformal				LogRemPaid				PS			
	Lag1	Lag2	Lag3	Lag4	Lag1	Lag2	Lag3	Lag4	Lag1	Lag2	Lag3	Lag4
Coef.	-0.1866167	0.3231224	0.242156	-0.2298259	-0.0069506	-0.0274914	-0.0216994	0.0212353	1.056557	-0.1708017	0.068969	0.0711855
Std. Err.	0.1853573	0.1414573	0.1483811	0.1071752	0.0441992	0.332004	0.0326128	0.0224317	0.944481	0.0684673	0.060654473	0.0587926
z	-1.01(0.314)	2.28*(0.022)	1.63(0.103)	-2.14*(0.032)	-0.16(0.875)	-0.83(0.408)	-0.67(0.506)	0.95(0.344)	11.19***(0.000)	-2.49*(0.013)	1.05(0.292)	1.21(0.226)
95% Conf.	-0.5499104	0.0458712	-0.0486657	-0.4398854	-0.0935795	-0.092563	-0.856194	-0.02273	0.8714417	-0.3049951	-0.0593054	-0.044046
Interval	0.176677	0.6003736	0.5329776	-0.0197663	0.0796783	0.0375801	-0.0422206	0.0652007	1.241672	-0.0366082	0.1972433	0.1864169

Granger test:

Equation \ Excluded	LogInformal			LogRemPaid			PS		
	LogRemPaid	PS	ALL	LogInformal	PS	ALL	LogInformal	LogRemPaid	ALL
chi2	2.182	8.385	11.875	22.884	1.581	28.204	19.944	3.188	21.255
df	4	4	8	4	4	8	4	4	8
Prob > chi2	0.702	0.078	0.157	0.000	0.812	0.000	0.001	0.527	0.006

Table 3.14

Correlation and causality in OECD Countries (Lag 5): remittances paid

Number Of observations: 580

Number of panels: 37

Ave. No. Of T: 15.676

	LogInformal					LogRemPaid					PS				
	Lag1	Lag2	Lag3	Lag4	Lag5	Lag1	Lag2	Lag3	Lag4	Lag5	Lag1	Lag2	Lag3	Lag4	Lag5
Coef.	1.325017	-0.4754586	0.1583701	-0.0433376	-0.0542619	-0.003631	-0.0001207	0.0162637	-0.0267733	0.0199812	0.0606999	-0.014885	0.0537215	-0.0822561	0.0584627
Std. Err.	0.843685	0.705436	0.0705411	0.0743664	0.0504474	0.163816	0.0114189	0.0083297	0.0087652	0.0082661	0.0419315	0.0028548	0.0245611	0.023058	0.205343
z	15.71***(0.000)	-6.74***(0.000)	2.25*(0.025)	-0.58(0.560)	-1.08(0.282)	-0.22(0.825)	-0.01(0.992)	1.95*(0.051)	-3.05**(0.002)	2.42*(0.016)	1.45(0.148)	-0.65(0.515)	2.19*(0.029)	-3.57***(0.000)	2.85**(0.004)
95% Conf.	1.159658	-0.6137216	0.20112	-0.189093	-0.153137	-0.0357383	-0.0225014	-0.0000623	-0.0439527	0.0037799	-0.0214843	-0.0596796	0.0055825	-0.1274489	82161
Interval	1.490376	-0.3371956	0.2966282	0.1024178	0.446131	0.0284763	0.2226	0.0325897	-0.0095939	0.0361825	0.1428841	0.0299097	0.1018604	-0.0370632	0.0987092

LogRemPaid

	LogInformal					LogRemPaid					PS				
	Lag1	Lag2	Lag3	Lag4	Lag5	Lag1	Lag2	Lag3	Lag4	Lag5	Lag1	Lag2	Lag3	Lag4	Lag5
Coef.	0.8917913	-0.2062752	0.175541	-0.0735742	0.0154987	0.8917913	-0.2062752	0.1757741	-0.0735742	0.0154987	0.355483	-0.0632403	0.1150646	-0.1956125	0.3006034
Std. Err.	0.1065391	0.1122547	0.1306703	0.0566529	0.0536463	0.1065391	0.1122547	0.1306703	0.0566529	0.0536463	0.1578861	0.109164	0.1066946	0.1780972	0.123362
z	8.37***(0.000)	-1.84*(0.66)	1.35(0.179)	-1.30(0.194)	0.29(0.773)	8.37***(0.000)	-0.184(0.066)	1.35(0.179)	-1.30(0.194)	0.29(0.773)	0.23(0.822)	-0.58(0.562)	1.08(0.281)	-1.10(0.272)	2.44*(0.015)
95% Conf.	0.6829786	-0.4262903	-0.080335	-0.1846118	-0.0896461	0.6829786	-0.4262903	-0.080335	-0.1846118	-0.0896461	-0.2739028	-2.771979	-0.094053	-0.5446767	0.0588182
Interval	1.100604	0.0137398	0.4318832	0.0374634	0.1206436	1.100604	0.0137398	0.4318832	0.0374634	0.1206436	0.3449994	0.1507173	0.3421822	0.1534517	0.5423885

PS

	LogInformal					LogRemPaid					PS				
	Lag1	Lag2	Lag3	Lag4	Lag5	Lag1	Lag2	Lag3	Lag4	Lag5	Lag1	Lag2	Lag3	Lag4	Lag5
Coef.	-0.0899776	0.2871059	0.2718226	-0.2488899	-0.0171771	-0.0172356	-0.0224928	-0.0308241	0.0196396	0.0111194	-1.011011	-0.1206461	0.0689153	0.0095652	0.0618045
Std. Err.	0.2248752	0.1579527	0.1632081	0.1611203	0.120808	0.0513708	0.0369548	0.0349018	0.0277344	0.0244743	0.1009161	0.0719365	0.0682557	0.0675827	0.0535521
z	-0.40(0.689)	1.82*(0.69)	1.67*(0.096)	-1.54(0.122)	-0.14(0.887)	-0.34(0.737)	-0.61(0.543)	-0.88(0.377)	0.71(0.479)	0.45(0.650)	10.02***(0.000)	-1.68*(0.094)	1.01(0.313)	0.14(0.887)	1.15(0.248)
95% Conf.	-0.5307249	-0.224758	-0.0480595	-0.5646798	-0.2539564	-0.1179205	-0.0949228	-0.0992305	-0.0347188	-0.0368493	0.813219	-0.2616391	-0.0648634	-0.1228945	-0.0431557
Interval	0.3507696	0.5966875	0.5917046	0.0669001	0.2196022	0.0834494	0.0499372	0.375822	0.0739979	0.0590882	1.208803	0.0203469	0.2026939	0.1420249	0.1667647

Granger test:

Equation \ Excluded	LogInformal			LogRemPaid			PS		
	LogRemPaid	PS	ALL	LogInformal	PS	ALL	LogRem	LogInformal	ALL
chi2	11.701	15.440	27.613	23.895	8.805	27.162	21.862	5.121	23.562
df	5	5	10	5	5	10	5	5	10
Prob > chi2	0.039	0.009	0.002	0.000	0.117	0.002	0.001	0.401	0.009

Table 3.15

Correlation and causality in in High Remittance-to-GDP Ratio Countries (Lag 1) $\frac{\boldsymbol{Rem}}{\boldsymbol{GDP}} > \mathbf{0.84}\%$.

Number Of observations: 745
Number of panels: 54
Ave. No. Of T: 13.796

	LogRem		
	LogRem	LogInformal	PS
	Lag1	Lag1	Lag1
Coef.	0.4380854	0.5680695	-0.1566762
Std. Err.	0.0920708	0.1135325	0.1135211
z	4.76***(0.000)	5.00***(0.000)	-1.38 (0.168)
95% Conf.	0.2576301	0.3455499	-0.3791734
Interval	0.6185408	0.790589	0.0658211

	LogInformal		
	LogRem	LogInf	PS
	Lag1	Lag1	Lag1
Coef.	0.0595111	0.0878931	-0.0257453
Std. Err.	0.254646	0.0371912	0.0293223
z	2.34* (0.019)	23.63***(0.000)	-0.88(0.380)
95% Conf.	0.0096013	0.8060376	-0.0832159
Interval	0.1094208	0.9518243	0.317253

	PS		
	LogRem	LogInformal	PS
	Lag1	Lag1	Lag1
Coef.	-0.0299883	0.0435274	0.9228176
Std. Err.	0.0430991	0.0684638	0.0504262
z	-0.70(0.487)	0.64(0.525)	18.30***(0.000)
95% Conf.	-0.114461	-0.0906592	0.8239839
Interval	0.0544844	0.1777141	1.021651

Granger test:

Equation \ Excluded	LogRem			LogInformal			PS		
	LogInformal	PS	ALL	LogRem	PS	ALL	LogRem	LogInformal	ALL
chi2	25.036	1.905	25.190	5.462	0.771	6.624	0.0484	0.404	0.488
df	1	1	2	1	1	2	1	1	2
Prob > chi2	0.000	0.168	0.000	0.019	0.380	0.036	0.487	0.525	0.784

Table 3.16

Correlation and causality in in High Remittance-to-GDP Ratio Countries (Lag 2) $\frac{Rem}{GDP} > \mathbf{0.84}\%$

Number Of observations: 710
Number of panels: 53
Ave. No. Of T: 13.396

	LogRem					
	LogRem		LogInformal		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.4454432	-0.0478839	0.6375815	-0.0173674	-0.1929972	-0.025104
Std. Err.	0.1099623	0.0436648	0.1699906	0.1475426	0.1227952	0.0722774
z	4.05***(0.000)	-1.10(0.237)	3.75***(0.000)	-0.12(0.906)	-1.57(0.116)	-0.35(0.728)
95% Conf.	0.2299211	-0.1334653	0.304406	-0.306547	-0.4336714	-0.1667652
Interval	0.6609652	0.0376975	0.970757	0.2718109	0.0476769	0.1165571

	LogInformal					
	LogRem		LogInformal		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.0815659	-0.0248709	1.046848	-0.1546316	0.0033993	-0.184519
Std. Err.	0.0311212	0.0114376	0.0644362	0.0513773	0.0303271	0.0246571
z	2.62**(0.009)	-2.17*(0.030)	16.25***(0.000)	-3.01**(0.003)	0.11(0.911)	-0.75(0.454)
95% Conf.	0.0205695	-0.0472882	0.920555	-0.2553293	-0.0560408	-0.0667788
Interval	0.1425623	- 0.0024536	1.17314	- 0.053934	0.0628394	0.0298751

	PS					
	LogRem		LogInformal		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	-0.0399399	0.126319	0.0275894	0.017858	0.9268125	-0.0125703
Std. Err.	0.049418	0.0260797	0.1135779	0.091277	0.0633693	0.0615407
z	- 0.81(0.419)	0.48(0.628)	0.24(0.808)	0.20(0.845)	14.63***(0.000)	-0.20(0.838)
95% Conf.	-0.1367975	-0.0384833	-0.1950192	-0.1610411	0.8026109	-0.1331878
Interval	0.0569177	0.0637471	0.250198	0.1967581	1.051014	0.1080471

Granger test:

Equation \ Excluded	LogRem			LogInformal			PS		
	LogInformal	PS	ALL	LogRem	PS	ALL	LogRem	LogInformal	ALL
chi2	26.518	2.882	27.147	8.116	0.574	9.083	0.719	0.382	0.865
df	2	2	4	2	2	4	2	2	4
Prob > chi2	0.000	0.327	0.000	0.017	0.750	0.059	0.698	0.826	0.930

Table 3.17

Correlation and causality in in High Remittance-to-GDP Ratio Countries (Lag 3) $\frac{\boldsymbol{Rem}}{\boldsymbol{GDP}} > \mathbf{0.84}\%$

Number Of observations: 653
Number of panels: 48
Ave. No. Of T: 13.604

	LogRem								
	LogRem			LogInformal			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.8084272	0.131424	-0.027523	0.7467665	-0.800278	-0.0896828	0.3490726	0.0794645	0.1801469
Std. Err.	0.0928195	0.0890016	0.040625	0.3362018	0.2597197	0.1394981	0.2426767	0.2788479	0.1567275
z	8.71***(0.000)	0.15(0.883)	-0.68(0.498)	2.22*(0.026)	-0.31(0.758)	-0.64(0.520)	1.44(0.150)	0.28(0.776)	1.15(0.250)
95% Conf.	0.6265044	-0.1612974	-0.1071466	0.0878231	-0.5890691	-0.363094	-0.1265649	-0.4670673	-0.1270335
Interval	0.99035	0.1875822	0.521007	1.40571	0.4290135	0.1837284	0.8247101	0.6259963	0.4873272

	LogInformal								
	LogRem			LogInformal			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.397596	0.022725	0.0013076	0.8644136	0.1030806	-0.115889	0.0098807	0.0051194	-0.0218082
Std. Err.	0.180119	0.144479	0.0076958	0.1264271	0.1238265	0.420691	0.0612486	0.0362416	0.0453687
z	2.21*(0.027)	0.16(0.875)	0.17(0.865)	6.84***(0.000)	0.78(0.438)	-2.75**(0.006)	0.16(0.872)	0.14(0.888)	-0.48(0.631)
95% Conf.	0.04457	-0.0260449	-0.0137759	0.6166211	-0.1572545	-0.198343	-0.1101643	-0.659128	-0.1107291
Interval	0.750622	0.305899	0.163911	1.112206	0.3634157	-0.033435	0.1299257	-0.761515	0.0671128

	PS								
	LogRem			LogInformal			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	-0.0178977	-0.0261308	0.0115601	-0.0781841	0.10993	-0.0779812	0.9631396	-0.1410037	0.0560198
Std. Err.	0.0288337	0.23060645	0.0146139	0.1085855	0.0948731	0.06612	0.0936306	0.0739742	0.0513676
z	-0.62(0.535)	1.13(0.257)	0.79(0.429)	-0.72(0.472)	1.16(0.247)	-0.18(0.238)	10.29***(0.000)	-1.91*(0.057)	1.09(0.275)
95% Conf.	-0.0744106	-0.190748	-0.0170827	-0.2910077	-0.0760179	-0.2075739	0.7796271	-0.2859906	-0.0446589
Interval	0.0386153	0.0713363	0.0402029	0.1346395	0.2958779	0.0516115	1.146652	0.0039831	0.1566985

Granger test:

Equation \ Excluded	LogRem			LogInformal			PS		
	LogInformal	PS	ALL	LogRem	PS	ALL	LogRem	LogInformal	ALL
chi2	8.900	10.411	14.393	9.234	0.280	11.335	3.335	2.467	5.753
df	3	3	6	3	3	6	3	3	6
Prob > chi2	0.031	0.015	0.026	0.026	0.964	0.079	0.343	0.481	0.451

Philosophy of database construction, variables definitions, data sources and sample of countries

The Philosophy of Database Construction

In our research, we constructed a panel dataset encompassing four geopolitical clusters: MENA (Middle East and North Africa), SSA (Sub-Saharan Africa), Latin America, and OECD (Organisation for Economic Co-operation and Development) countries. This task was inherently complex, requiring the identification of consistent variables and datasets across these diverse regions.

The selected observation period spans from 1996 to 2017. This period was chosen for several reasons. First, data on remittances, the informal sector, and political stability are completer and more consistent from 1996 onwards. Second, this period covers significant phases of globalization, economic crises, and political changes that strongly influence the dynamics studied. Finally, a period of more than 20 years allows for capturing long-term trends and economic and political dynamics that are not visible over shorter periods.

The database comprises 1373 observations spread over 82 panels, with an average of 17.217 observations per panel. The main variables used include remittances (logarithmic), the informal sector (logarithmic), and political stability. The data have been normalized to ensure comparability and robust analysis.

We used data on remittances, political stability, and GDP from the World Bank. For information on the informal sector, we drew inspiration from the work of Medina and Schneider (2019), who developed a database covering 157 countries from 1991 to 2017. To harmonize these data with other variables in our study, we selected data starting from 1996, due to incomplete data on political stability from 1991 to 1995. This approach allowed us to compile a balanced panel database integrating all variables from various sources for the period between 1996 and 2017.

The data from Medina and Schneider on the informal sector, expressed as percentages, were recalculated in our study for better clarity. We multiplied this percentage of the informal sector by GDP (in US dollars) as reported by the World Bank, applying the logarithm of this ratio, along with the log of remittances, to enhance interpretability. To verify the integrity of our dataset, we conducted several statistical tests. A collinearity assessment, based on a rule of thumb, indicated that multicollinearity does not significantly affect most of our regression models. To explore causality in the sense of Granger, we ensured our dataset's stationarity. Through a stationarity test based on eigenvalue conditions, we confirmed that our Panel Autoregressive Model meets the requisite stability conditions.

Collecting reliable and complete data on the informal sector was a major challenge due to its unreported nature. We opted for the MIMIC (Multiple Indicators, Multiple Causes) method provided by Medina and Schneider (2019) to estimate the size of the informal sector. Harmonizing data from different sources required particular attention to ensure their consistency and comparability. To overcome potential causality issues, we used the Panel Vector Autoregressive (PVAR) model and the Granger causality test to better understand the dynamic relationships between the variables.

The database for this study was constructed with meticulous attention to the quality and consistency of the data. The methodological choices and observation periods were selected to maximize the relevance and robustness of the results. By overcoming various challenges in data collection and harmonization, this database provides a solid foundation for analyzing the dynamics between remittances, the informal sector, and political stability across different geopolitical contexts.

Figure 3.4

Cartography of sample countries

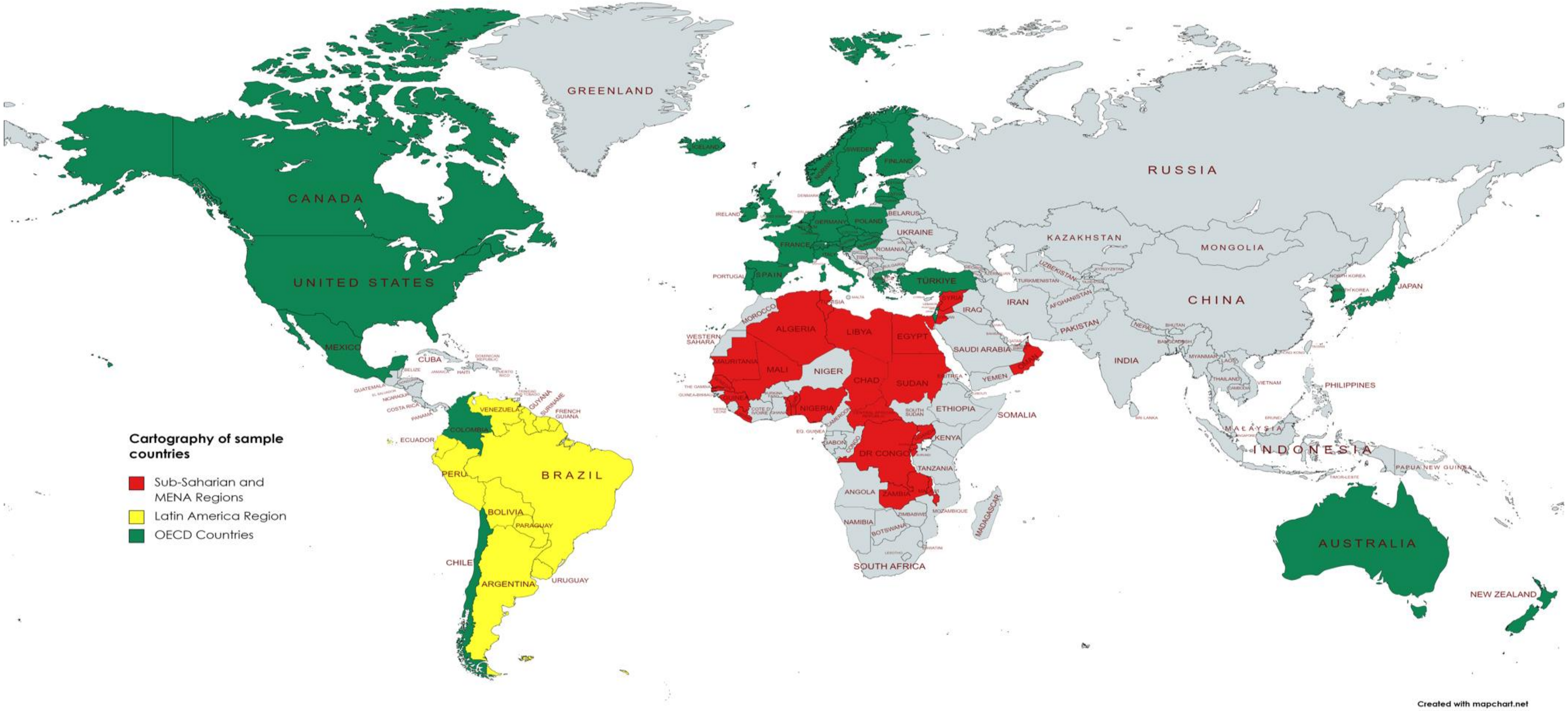


Table 3.18

List of countries

MENA and Sub-Saharan Africa region:

1 - Algeria	11 - Lebanon	21 – Syrian Arab Republic
2 - Benin	12 - Liberia	22 - Togo
3 - Burundi	13 - Libya	23 - Tunisia
4 - Central African Republic	14 - Malawi	24 - Uganda
5 - Chad	15 - Mali	25 - Zambia
6 - Congo. Dem. Rep.	16 - Mauritania	
7 - Egypt. Arab Rep.	17 - Nigeria	
8 - Gambia. The	18 - Oman	
9 - Guinea	19 - Rwanda	
10 - Jordan	20 - Senegal	

Latin America region:

1 - Argentina	11 - Guatemala	21 – Uruguay
2 - Bahamas	12 - Guyana	22- Venezuela
3 - Bolivia	13 - Haiti	
4 - Brazil	14 - Honduras	
5 - Chile	15 - Jamaica	
6 - Colombia	16 - Mexico	
7 – Costa Rica	17 - Nicaragua	
8 – Dominican Republic	18 - Paraguay	
9 - Ecuador	19 - Peru	
10 – El Salvador	20 – Trinidad and Tobago	

Optimal lag analysis

Each lag indicates how far back in time the variables are being analyzed to predict future values. Here's a breakdown of the columns and what each metric represents:

Columns Explanation

- Lag: The number of time periods used to shift the data for the analysis.
- CD (Cross-correlation Decay): Indicates the degree to which correlations between variables decrease as the lag increases. Values close to 1 suggest little decay, indicating that earlier data points remain highly relevant.
- J: The test statistic value for a specific test (not specified but often related to testing for serial correlation or another time-series property).
- J pvalue: P-value associated with the J test statistic, indicating the probability of observing the test results under the null hypothesis.
- MBIC (Modified Bayesian Information Criterion): A criterion for model selection among a finite set of models; lower values indicate better models, with adjustments to penalize more complex models.
- MAIC (Modified Akaike Information Criterion): Similar to MBIC, it's another model selection criterion that penalizes less harshly for model complexity.
- MQIC (Modified Hannan-Quinn Information Criterion): Also used for model selection, providing a balance between MBIC and MAIC in terms of penalizing model complexity.

Table 3.19

Optimal lag, Sub-Saharan Africa and MENA region

Number Of observations: 339
Number of panels: 22
Ave. No. Of T: 15.409

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.9999647	24.58146	0.597905	-132.7205	-29.41854	-70.5844
2	0.9999646	17.52127	0.487583	-87.34674	-18.47873	-45.92264
3	0.99996	11.54558	0.2401556	-40.88842	-6.454417	-20.17637

The table 23 provides statistical metrics for selecting the optimal lag in a time-series analysis specifically for the Sub-Saharan Africa (SSA) and Middle East and North Africa (MENA) regions.

Interpretation and Selection of Optimal Lag

- CD (Cross-correlation Decay): Across all lags, the CD value is very close to 1, indicating that correlations are maintained even with increasing lags, suggesting a strong persistent relationship in the data across time periods.
- J and J p-value: Lower J values and higher p-values (as seen from lag 1 to 3) suggest decreasing statistical significance in terms of the model's ability to predict future values based on past values. This implies that as we incorporate more past data (increasing lag), it becomes less statistically significant in explaining future variations.
- Information Criteria (MBIC, MAIC, MQIC):
  - Lag 1: Offers the lowest (most negative) values for MBIC, MAIC, and MQIC, suggesting that it provides the best fit among the tested models with the least penalty for model complexity.
  - Lag 2 and 3: Show increasing values in MBIC, MAIC, and MQIC, indicating that adding more lags leads to models that fit worse, even after adjusting for complexity.

Given this data, Lag 1 is the optimal choice for analyzing time-series data in SSA and MENA for this study. It provides the best balance between model fit and complexity according to the information criteria and maintains statistical significance according to the J statistic and its associated p-value. This suggests that looking one period back provides the most relevant and significant insight into future values without unnecessarily complicating the model with data that do not add predictive value.

Given the MBIC, MAIC, and MQIC values, along with the J p-values, the choice of Lag 1 can be economically justified as it offers a balance between capturing essential economic dynamics and maintaining model parsimony and robustness. This choice is particularly appropriate in the SSA and MENA context, where annual economic fluctuations are closely tied to national and international economic policies, and where economic modelling needs to remain adaptable and robust against frequent economic and political changes.

Table 3.20

Optimal lag, Latin America region

Number Of observations: 332
Number of panels: 21
Ave. No. Of T: 15.810

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.9999951	21.24601	0.7746324	-135.4926	-32.75399	-73.7261
2	0.9999945	12.18899	0.837328	-92.30344	-23.81101	-51.12575
3	0.9999933	8.435541	0.4909184	-43.81067	-9.564459	-23.22183

Analysis of Results

- Lag 1 offers the lowest MBIC, which means it is the most preferred model according to the Bayesian Information Criterion modified for panel data. It has considerably lower MBIC values compared to other lags, suggesting that including only one lag minimizes information loss while adequately capturing the data dynamics under the Bayesian framework.
- Lag 3 has the highest J p-value, which might seem to indicate a good model fit from the perspective of instrument validity, but its information criteria values are much higher (worse) than those for Lag 1.
- Lag 2 has a higher J p-value than Lag 1 but its information criteria scores are not as low as those for Lag 1.

Given the MBIC, MAIC, and MQIC values along with the J p-values, Lag 1 appears to be the optimal choice for our model. It provides a balance between model simplicity and fit, suggesting that it sufficiently captures the dynamics in the data with the least complexity, hence minimizing the risk of overfitting while maintaining robustness and validity of the instruments used in the model. This choice would generally be considered the most prudent based on these criteria, particularly noting the substantial drop in MBIC from Lag 2 to Lag 1.

Given the MBIC, MAIC, and MQIC values, along with the J p-values, the choice of Lag 1 can be economically justified as it offers a balance between capturing essential economic dynamics and maintaining model parsimony and robustness. This choice is particularly appropriate in the Latin American context, where annual economic fluctuations are closely tied to national and international economic policies, and where economic modelling needs to remain adaptable and robust against frequent economic and political changes.

Table 3.21

Optimal lag, OECD region

Number Of observations: 448
Number of panels: 38
Ave. No. Of T: 11.789

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.9999976	72.36982	5.12e-06	-92.4596	18.36982	-25.32019
2	0.9999985	29.18498	0.461647	-80.7013	-6.815021	-35.94169
3	0.999998	20.58191	0.0146419	-34.36123	2.581911	-11.98143

Optimal Lag Selection

The results indicate varying recommendations from different criteria:

- **MBIC** suggests a more parsimonious model is better, showing its lowest value at lag 2.
- **MAIC** and **MQIC** show their lowest values at different lags, with MQIC also suggesting lag 2 as optimal, considering it gives a good balance between fitting complexity and maintaining parsimony.

Given these observations, **lag 2** might be considered optimal based on the MBIC and MQIC values. Lag 2 also shows a significant improvement in the J p-value compared to lag 1, suggesting that adding the second lag helps in addressing instrument validity without overly complicating the model.

Choosing lag 2 is economically justified as it likely captures the medium-term effects and cyclic dynamics inherent in OECD economies. It may reflect the different roles remittances play in more developed economies, potentially influencing more strategic economic decisions rather than mere survival strategies.

Choosing a lag of 2 is not only statistically justified based on model fit and validity criteria but also economically sensible given the typical economic behaviors, policy response times, and data characteristics in OECD countries[5].

Table 3.22

Optimal lag, OECD region, Remittances Paid

Number Of observations: 617
Number of panels: 37
Ave. No. Of T: 16.676

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.9999727	109.3687	7.09e-12	-64.10281	55.36865	8.919134
2	0.9999792	34.6483	0.0104631	-80.99934	-1.3517	-32.31804
3	0.9999753	26.13722	0.00194	-31.6866	8.13722	-7.345952

Lag Order Selection:

- **Lag 1**: Shows a very low J p-value, indicating significant problems with the model/instruments at this lag.
- **Lag 2**: Significantly improved over lag 1 in terms of the J-statistic and its p-value (.0102095), indicating that instruments are more valid here. MBIC shows a considerable improvement, suggesting that adding the second lag helps in better capturing the dynamics in the data.

[5] **Economic and policy response delays**: Economic processes and policy responses typically do not materialize instantly but rather unfold over time. A lag of 2 years can capture these delayed responses, providing a more realistic model of economic interactions and policy impacts. For example, changes in the informal sector might influence migration patterns or political stability over a period extending beyond just the immediate past year.

Business cycles: OECD countries generally experience business cycles that can last several years. Incorporating at least two lags allows the model to account for mid-cycle adjustments in the economic variables, better reflecting the cyclic nature of economic activity and its impact on variables like informal sector size, remittances, and political stability.

Data collection and reporting delays: In the context of macroeconomic data, there are often delays in data collection, processing, and reporting. A lag of 2 years helps mitigate the impact of these delays on the analysis, ensuring that the effects of any late-reported changes are adequately captured.

- **Lag 3**: Although the J-statistic continues to improve, suggesting better instrument validity, the MBIC increases compared to lag 2, indicating that the additional complexity might not be justified despite the acceptable J p-value.

Optimal Lag:

Given these results, **Lag 2** appears to be the most appropriate choice for further analysis:

- **Validity**: The significant improvement in J-statistic and its p-value at lag 2 compared to lag 1 implies that instruments are valid and the model fits the data better.

- **Information criteria**: The MBIC at lag 2 is considerably lower than at lag 1 and lag 3, suggesting an optimal balance between model complexity and fit.

Implications for Modeling:

With the chosen lag of 2, our PVAR model would appropriately balance capturing the data's dynamics without overfitting, considering the panel and temporal dimensions of our dataset. This lag structure allows for assessing the impacts of variables with up to two periods of lag, which can be critical when examining the relationships in economic data, where effects might not be immediate but occur over time. This model setup is particularly suited to further investigate how variables like the size of the informal sector, remittance flows, and political stability interact in the context of OECD countries over this period.

Table 3.23

Optimal lag, High Remittance-to-GDP Ratio Countries ($\frac{\boldsymbol{Rem}}{\boldsymbol{GDP}} > \mathbf{0.84}\%$)

Number Of observations: 642
Number of panels: 52
Ave. No. Of T: 12.346

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.999997	45.771	0.013464	-128.7729	-8.229004	-55.01133
2	0.9999974	28.69581	0.0522258	-87.66678	-7.304192	-38.49241
3	0.9999844	16.43617	0.0583133	-41.74512	-1.563829	-17.15794

Interpretation of Results

- Lag 1 :
  - Has the highest J statistic and the lowest J p-value, suggesting some issues with instrument validity compared to other lag choices.

    - Offers the best MBIC score, indicating it's the most parsimonious model according to this criterion.
- Lag 2 :
    - Sees a reduction in the J statistic and an increase in the J p-value, suggesting improved instrument validity.
    - The MBIC increases (less negative), indicating a less parsimonious model compared to Lag 1.
- Lag 3 :
    - Continues the trend with a further reduced J statistic and slightly better J p-value, suggesting continued improvement in instrument validity.
    - The MBIC score further reduces its negative value, suggesting increasing complexity without enough justification in data fitting or prediction improvement over Lag 1.

The choice of lag should balance model complexity with the ability to capture enough of the data dynamics and the validity of instruments. While Lag 1 provides the best MBIC and is the simplest model, it has the lowest p-value for the J statistic, suggesting possible issues with instrument validity. On the other hand, Lag 3, while offering better instrument validity, significantly increases model complexity as seen in the less favorable MBIC score.

Given this, Lag 2 might be a reasonable compromise, offering improved instrument validity over Lag 1 with a moderate increase in model complexity, and still maintaining a better balance according to the MBIC compared to Lag 3. But economics considerations lead us to choose 1.

Stationarity test: Eigenvalue stability condition

The Eigenvalue stability condition in appendix 4 provide the part of the stability analysis for a Panel Vector Autoregression (PVAR) model. This analysis is crucial for assessing whether the model is dynamically stable and whether the inferences drawn from it about the long-term relationships and impacts are valid. Here is what the table means and its implications:

Understanding Eigenvalues in PVAR Stability

- Eigenvalue: Each eigenvalue of the model's companion matrix indicates the stability of a particular dynamic process within the PVAR system. The eigenvalue is composed of a real part and an imaginary part, with the modulus (absolute value) reflecting the distance of the eigenvalue from the origin in the complex plane.
- Real part: Indicates the speed of the response in the system. A real part closer to 1 indicates a slower decay of the effect of shocks.
- Imaginary part: Indicates the oscillatory behavior of the system. A NO-zero imaginary part suggests cyclical behavior.
- Modulus: The critical measure for stability. For the PVAR model to be stable, the modulus of each eigenvalue must be less than 1.

Given our model's stability, we can proceed with analyzing the dynamic responses of these variables to different shocks (e.g., through impulse response functions) or conduct scenario analyses to explore how changes in one variable might affect others over time. This kind of analysis can be particularly useful for examining the impacts of potential policy changes or external economic shocks.

Table 3.24

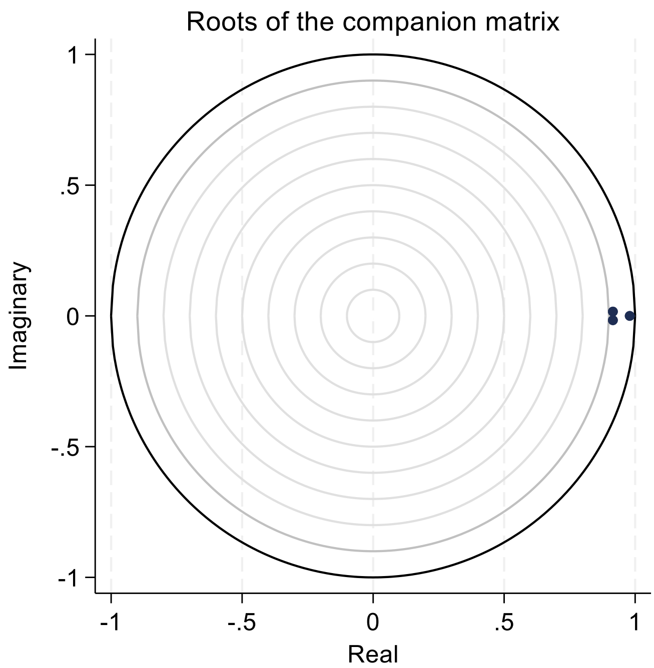
Stationarity test: Eigenvalue stability condition, Sub-Saharan Africa and MENA region

Eigenvalue		
Real	Imaginary	Modulus
0.9794008	0	0.9794008
0.9151533	0.0164215	0.9153006
0.9151533	-0.0164215	0.9153006

All the eigenvalues lie inside the unit cercle.
pVAR satisfies stability condition.

Figure 3.5

Eigenvalue stability condition, Sub-Saharan Africa and MENA region



Stability condition

- Eigenvalues listed:
    - The first eigenvalue has a modulus of approximately 0.979 and is real, indicating a stable, NO-oscillatory process.
    - The next two eigenvalues are complex conjugates of each other (as seen from the imaginary parts being positive and negative versions of the same number), with a

modulus of about 0.915. The presence of the imaginary component suggests that this part of the system exhibits cyclical behavior, but since the modulus is less than 1, these cycles dampen over time, contributing to overall system stability.

- Condition met: All the eigenvalues have moduli less than 1, which confirms that all dynamic responses within the PVAR system decay over time rather than exploding, ensuring the model's stability.

Implications for SSA and MENA Regions

Given that the PVAR model is stable:

- Long-term predictions: The model can reliably be used for forecasting and analyzing long-term relationships within the data. This is crucial for policy planning and economic forecasts in the SSA and MENA regions, where economic dynamics are influenced by factors like remittances, informal sector activities, and political stability.
- Dynamic responses: The model's ability to highlight the impact of a shock in one variable on others over time is validated. For instance, understanding how shocks to remittances affect political stability or the size of the informal sector can help in crafting policies that mitigate negative impacts or enhance positive ones.
- Cyclical behavior: The cyclical behavior indicated by the complex eigenvalues suggests that some economic phenomena in these regions might undergo regular ups and downs, which could influence policy timing and focus.

Overall, the stability of the PVAR model means that it provides a reliable tool for economic analysis and decision-making in regions characterized by complex interdependencies between economic factors.

Table 3.25

Stationarity test: Eigenvalue stability condition, Latin America region

Eigenvalue		
Real	Imaginary	Modulus
0.9615227	0	0.9615227
0.8527042	0	0.8527042
0.1576935	0	0.1576935

All the eigenvalues lie inside the unit cercle.
p-VAR satisfies stability condition.

Eigenvalues analysis:

- Real Part: All eigenvalues are real numbers (no imaginary part), which simplifies the interpretation. The presence of real eigenvalues implies oscillations or responses that either damp out over time or converge without oscillating.

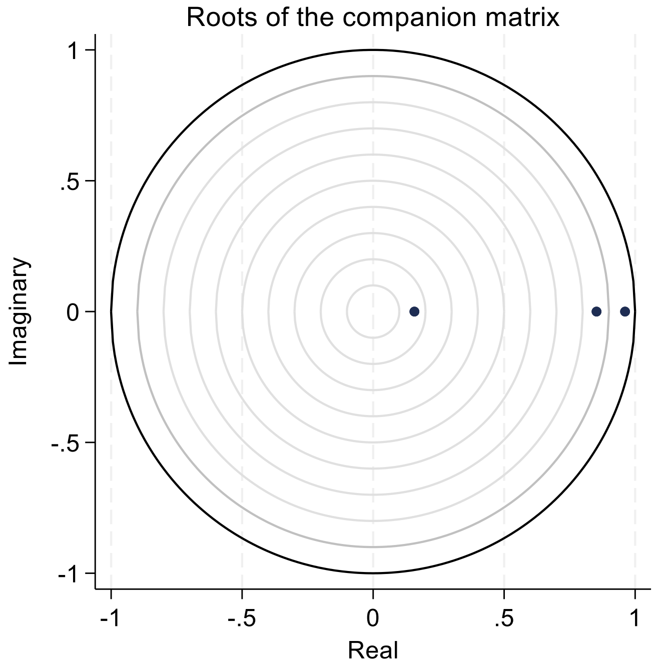
- Modulus: Each eigenvalue's modulus (absolute value) is less than 1, which is exactly what we want for a stable VAR model. The eigenvalues reported are 0.9615227, 0.8527042, and 0.1576935.

    - The eigenvalue of 0.9615227, while close to 1, still lies within the unit circle, indicating that any impact from shocks to the system will eventually dampen rather than increase over time.

    - The lower moduli (0.8527042 and 0.1576935) suggest quicker damping of shocks to those components of the system, implying that some variables in the model respond to shocks more rapidly than others.

Figure 3.6

Eigenvalue stability condition, Latin America region



Given this model's stability, we can proceed with analyzing the dynamic responses of these variables to different shocks (e.g., through impulse response functions) or conduct scenario analyses to explore how changes in one variable might affect others over time. This kind of analysis can be particularly useful for examining the impacts of potential policy changes or external economic shocks on the Latin American region.

Table 3.26

Stationarity test: Eigenvalue stability condition, OECD region

Eigenvalue		
Real	Imaginary	Modulus
0.8719101	0	0.8719101
0.752251	0	0.752251
0.5506327	-0.1985913	0.5853503
0.5506327	0.1985913	0.5853503
0.1414062	0.1379768	0.1975685
0.1414062	-0.1379768	0.1975685

All the eigenvalues lie inside the unit cercle.
pVAR satisfies stability condition.

- Eigenvalues listed:
    - The eigenvalues we've provided all have moduli less than 1, as indicated by the highest modulus being 0.8719101. This suggests that the system is stable.
    - Real components are dominant in our eigenvalues, showing that the dynamics mainly involve growth or decay rather than oscillatory behavior.
- Complex eigenvalues:
    - The presence of complex eigenvalues (those with NO-zero imaginary parts) indicates oscillatory behavior in the dynamics of the variables. This can reflect cyclical patterns in the data, such as seasonal effects or business cycles.

The fact that all eigenvalues lie within the unit circle confirms that our PVAR model satisfies the stability condition, suggesting that the model is appropriately specified to capture the dynamics among remittances, the informal sector size, and political stability without leading to explosive or divergent behaviors. This stability is crucial for reliable simulations and forecasts based on the model, as it ensures that the dynamic responses to shocks are both realistic and bounded over time.
In practical terms, this stability allows policymakers and researchers to trust the model's predictions about how changes in one variable might impact others in the system, making

it a valuable tool for economic analysis and policy planning in the context of OECD countries.

Figure 3.7

Eigenvalue stability condition, OECD region

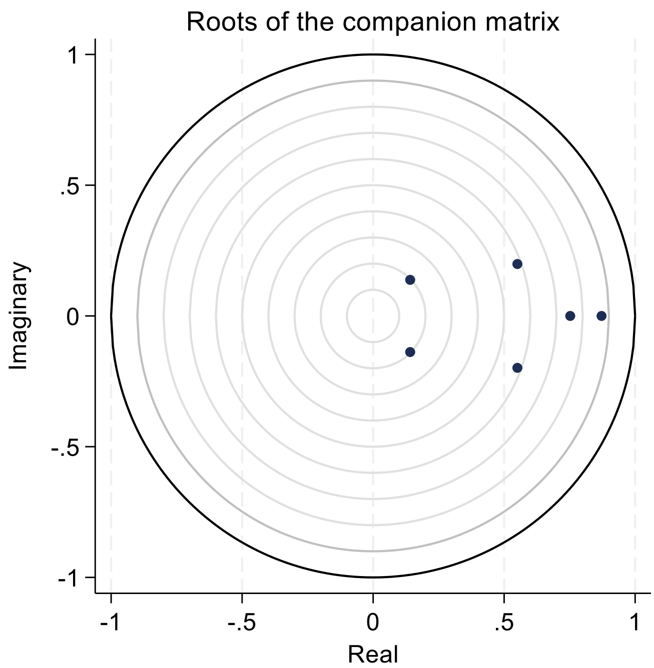


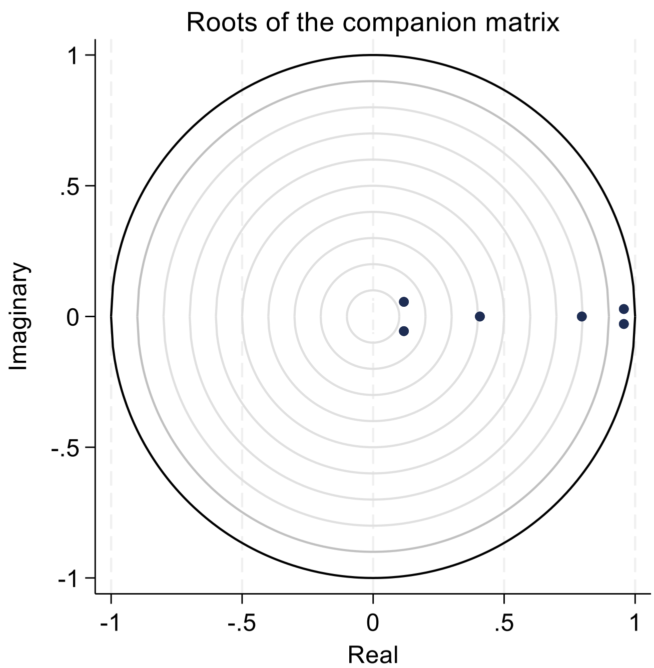
Table 3.27

Stationarity test: Eigenvalue stability condition, OECD region, Remittances Paid

Eigenvalue		
Real	Imaginary	Modulus
0.956965	0.0286112	0.9573927
0.956965	-0.0286112	0.9573927
0.7965988	0	0.7965988
0.4074795	0	0.4074795
0.117326	0.0559841	0.1299986
0.117326	-0.0559841	0.1299986

All the eigenvalues lie inside the unit cercle.
pVAR satisfies stability condition.

Figure 3.8: Eigenvalue stability condition, OECD region, Remittances Paid



Eigenvalue stability condition

- **Eigenvalues and modulus**:
  - The stability of a PVAR model is generally assessed by examining the eigenvalues of its associated companion matrix. The critical condition for

stability is that all eigenvalues must have moduli (absolute values) less than one.

- The modulus of each eigenvalue reflects the speed at which effects from shocks to the system decay over time. A modulus less than one suggests that the effects of a shock will diminish, leading to stable dynamic responses in the model.

- **Interpretation of our results**:

  - All the eigenvalues listed have moduli less than one, as shown in the column labeled "Modulus". This indicates that over time, any perturbation to the system (e.g., a shock to one of the variables like a sudden change in remittances or political stability) will eventually die out, leading the system back to its equilibrium.

  - Eigenvalues close to one, such as .956407, suggest that some dynamic responses in our model may persist longer before they decay, indicating that shocks may have relatively enduring effects but will still stabilize over time.

  - Lower moduli, like .4077992, imply that shocks to those components of the system dissipate more quickly.

- **Implications for economic analysis**

  - **Model reliability**: Since our PVAR model satisfies the eigenvalue stability condition, it is reliable for forecasting and impulse response analysis. This reliability is crucial for policy simulation and economic forecasting in the context of OECD countries, where accurate predictions of economic dynamics are essential for policy planning.

  - **Policy insights**: The stability of the model allows policymakers and researchers to use the model's predictions confidently, knowing that the model accurately represents the long-run behavior of the system. This is particularly useful for evaluating the impacts of potential policy changes on the informal sector, remittances, and political stability.

  - **Dynamic analysis**: With a stable model, impulse response functions (IRFs) can be meaningfully interpreted. These IRFs will show how a shock to one variable (e.g., a sudden increase in remittances) will affect other variables in the system over time, providing insights into the transmission mechanisms within the economy.

The confirmation that all eigenvalues lie inside the unit circle and that the PVAR satisfies the stability condition means that our model is well-suited for further analysis and can be reliably used to study dynamic interactions among the size of the informal sector, remittance flows, and political stability in OECD countries. This enables both short-term and long-term economic and policy analyses, making it a valuable tool for researchers and policymakers alike.

Table 3.28

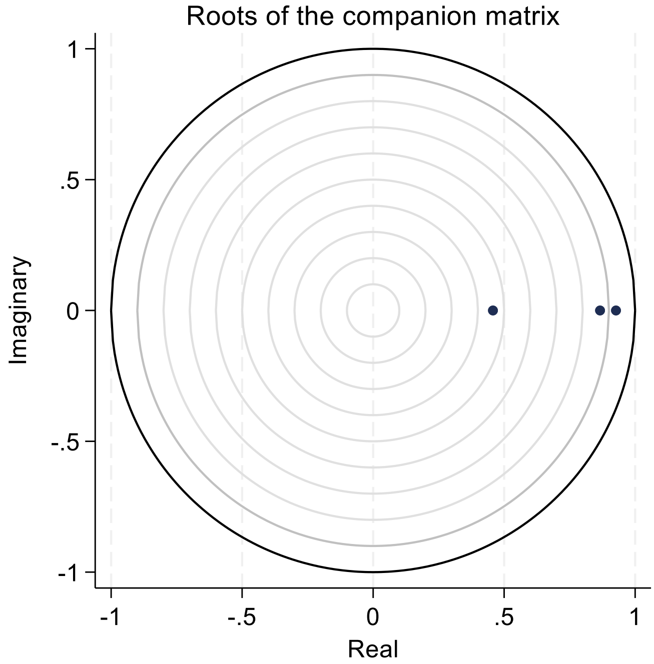
Stationarity test: Eigenvalue stability condition, High Remittance-to-GDP Ratio Countries ($\frac{Rem}{GDP} > \mathbf{0.84}\%$*)*

Eigenvalue		
Real	Imaginary	Modulus
0.9354819	-0.0143186	0.9355915
0.9354819	0.0143186	0.9355915
0.3741746	0	0.3741746

All the eigenvalues lie inside the unit cercle.
pVAR satisfies stability condition.

Figure 3.9

Eigenvalue stability condition, High Remittance-to-GDP Ratio Countries ($\frac{Rem}{GDP} > \mathbf{0.84}\%$*)*



Interpretation of Results

- The eigenvalues presented are 0.9269379, 0.8661825, and 0.4573094. All these values are less than 1.
- **Stability**: Since all eigenvalues have moduli less than 1, this indicates that the PVAR model satisfies the stability condition. This is a good sign as it implies that

the impacts of shocks to the variables in the model will dissipate over time rather than increase or oscillate indefinitely.

Implications

- **Model dynamics**: The model is stable, suggesting that it appropriately captures the dynamics among the variables (log of informal sector size, log of remittances, and political stability) without leading to explosive predictions.
- **Forecasting and inference**: Stability ensures that the model can be used for forecasting and policy inference within the bounds of the data and model specifications used, without concerns about the results diverging over time.

The graphical representation of these results, usually displayed in a root locus plot, visually confirm that the eigenvalues are within the unit circle. This plot is provided in figure9.

Collinearity diagnostics

The Variance inflation factors (VIF) range from 1 upwards. The numerical value for VIF tells us (in decimal form) what percentage the variance is inflated for each coefficient. For example, a VIF of 1.9 tells that the variance of a particular coefficient is 90% bigger than what we would expect if there was no multicollinearity if there was no correlation with other predictors.

A **rule of thumb** for interpreting the variance inflation factor:

- 1 = not correlated.
- Between 1 and 5 = moderately correlated.
- Greater than 5 = highly correlated.

$$VIF = \frac{1}{1 - R_i^2}$$

Table 3.29

Collinearity diagnostics (SSA and MENA region)

Nb of observations : 457

Variable	VIF	SQRT VIF	Tolerance	R-Squared
PS	1.04	1.02	0.9589	0.0411
LogInformal	1.77	1.33	0.5657	0.4343
LogRem	1.72	1.31	0.5819	0.4181
Mean VIF	1.51			

	Eigenval	Cond Index
1	3.3945	1.0000
2	0.5942	2.3901
3	0.0102	18.2372
4	0.0011	54.9271
Condition Number		54.9271

Note: Eigenvalues and Cond Index computed from scaled sscp (w/ intercept)

Det(correlation matrix) 0.5655

Table 25 shows statistics related to multicollinearity diagnostics and condition indexes for a model involving the variables: Political Stability (PS), logarithm of informal sector size (LogInformal), and logarithm of remittances (LogRem). Here's a breakdown of these statistics and what they imply about the data model:

Multicollinearity diagnostics

Variance Inflation Factor (VIF): Measures how much the variance of a regression coefficient is inflated due to multicollinearity in the model.

- PS: VIF is 1.04, suggesting very little inflation and thus minimal multicollinearity with other variables.
- LogInformal: VIF is 1.77, indicating some moderate multicollinearity.
- LogRem: VIF is 1.72, also indicating moderate multicollinearity.
- SQRT VIF: The square root of VIF, easier to interpret directly as a factor of inflation.
- Tolerance: The inverse of VIF, representing the proportion of variance in the predictor not explained by other predictors.
- R-Squared: Proportion of variance in the predictor explained by other predictors.
- The Mean VIF of 1.51 suggests that, on average, the variables show a low to moderate level of multicollinearity. Usually, a VIF above 5 is cause for concern, so these levels are generally acceptable.

Table 3.30

Collinearity diagnostics (Latin America region)

Nb of observations : 443

Variable	VIF	SQRT VIF	Tolerance	R-Squared
PS	1.11	1.05	0.8992	0.1008
LogRem	1.30	1.14	0.7676	0.2324
LogInformal	1.20	1.09	0.8349	0.1651
Mean VIF	1.20			

	Eigenval	Cond Index
1	3.2953	1.0000
2	0.6992	2.1710
3	0.0039	29.0822
4	0.0016	44.7930
Condition Number		44.7930

Note: Eigenvalues and Cond Index computed from scaled sscp (w/ intercept)

Det(correlation matrix) 0.7510

Interpretation of collinearity diagnostics

- Variance Inflation Factor (VIF):
    - loginf: VIF of 1.20 suggests a low level of multicollinearity.
    - logrem: VIF of 1.30 also indicates minimal multicollinearity.
    - ps: VIF of 1.11 shows very low multicollinearity.
    - The Mean VIF across all variables is 1.20, which is well below the common threshold of 5 or 10, indicating that multicollinearity is generally not a concern for these variables.
- Tolerance:

Values are all above 0.7 (ranging from 0.7676 to 0.8992), which further confirms that multicollinearity is not severe, as lower values (below 0.1 or 0.2) would indicate potential problems.

- R-Squared:

The R-squared values are relatively low (all below 0.25), suggesting that NOe of these variables is highly predictable from the others.

- Condition Number:

The condition index of 44.7930 points to a potential issue. A rule of thumb is that condition indices above 30 may indicate multicollinearity that could be problematic, particularly with the presence of small eigenvalues (as seen here with 0.0039 and 0.0016). The presence of a very small eigenvalue (0.0016) and a high condition index suggests that despite the low VIF and R-squared values, there might be a specific combination of linear dependencies that could potentially affect estimates or make the model sensitive to small changes in the data.

- Implications

The overall diagnostics suggest that while individual multicollinearity is not a concern, the high condition index accompanied by very small eigenvalues might indicate some deeper, less apparent collinearity issues, possibly associated with specific linear combinations of the predictors. This could be influenced by the structure of our data or the relationships among variables in Latin American economies.

Table 3.31

Collinearity diagnostics (OECD countries)

Variable	VIF	SQRT VIF	Tolerance	R-Squared
LogInformal	1.90	1.38	0.5266	0.4734
LogRem	1.85	1.36	0.5418	0.4582
PS	1.08	1.04	0.9264	0.0736
Mean VIF	1.61			

Nb of observations : 642

	Eigenval	Cond Index
1	3.5417	1.0000
2	0.4551	2.7896
3	0.0021	40.9326
4	0.0011	57.9763
Condition Number		57.9763

Note: Eigenvalues and Cond Index computed from scaled sscp (w/ intercept)

Det(correlation matrix) 0.5028

For OECD countries, loginf has a VIF of 1.90 and a tolerance of 0.5266, logrem has a VIF of 1.85 and a tolerance of 0.5418, and ps has a VIF of 1.08 and a tolerance of 0.9264. These values indicate a moderate level of multicollinearity for loginf and logrem, but less so for ps.

Table 3.32

Collinearity diagnostics (OECD countries),), Remittances Paid

Nb of observations : 809

Variable	VIF	SQRT VIF	Tolerance	R-Squared
logrempaid	1.56	1.25	0.6430	0.3570
loginf	1.61	1.27	0.6196	0.3804
ps	1.05	1.02	0.9530	0.0470
Mean VIF	1.41			

	Eigenval	Cond Index
1	3.5946	1.0000
2	0.3994	2.9999
3	0.0052	26.2582
4	0.0008	69.0915
Condition Number		69.0915

Note: Eigenvalues and Cond Index computed from scaled sscp (w/ intercept)

Det(correlation matrix) 0.6188

Variance Inflation Factor (VIF):

- **loginf:** VIF of 1.61 indicates a moderate level of collinearity.
- **logrempaid:** VIF of 1.56 also indicates a moderate level.
- **ps:** VIF of 1.05 suggests minimal collinearity with other variables.
- **Mean VIF:** The average VIF across the variables is 1.41, which is generally considered low to moderate, suggesting that multicollinearity is not a severe concern in this model.

Table 3.33

Collinearity diagnostics, High Remittance-to-GDP Ratio Countries ($\frac{Rem}{GDP} > \mathbf{0.84}\%$)

Nb of observations : 847

Variable	VIF	SQRT VIF	Tolerance	R-Squared
logrem	3.31	1.82	0.3022	0.6978
loginf	3.32	1.82	0.3013	0.6987
ps	1.01	1.00	0.9948	0.0052
Mean VIF	2.54			

	Eigenval	Cond Index
1	3.0606	1.0000
2	0.9356	1.8087
3	0.0031	31.4537
4	0.0007	68.5391
Condition Number		68.5391

Note: Eigenvalues and Cond Index computed from scaled sscp (w/ intercept)

Det(correlation matrix) 0.3008

Table 37 provides the collinearity diagnostics in High Remittance-to-GDP Ratio Countries.

- **loginf** and **logrem** have VIFs around 3.3, which is moderately high and suggests some level of multicollinearity, although typically VIF values above 5 or 10 are considered indicative of serious multicollinearity concerns.

- **ps** has a VIF very close to 1, indicating almost no collinearity with the other variables.

The diagnostics suggest that **loginf** and **logrem** are likely to be collinear. This can impact the precision of the estimates in regression analysis, leading to wider confidence intervals and less reliable p-values. **ps** does not exhibit such issues. The relatively high mean VIF, coupled with a low determinant of the correlation matrix (0.3008), confirms that the model's predictors do not provide completely independent information about the response variable.

- **Further analysis**: It might be necessary to reconsider the model specification, perhaps by removing one of the collinear variables or using techniques such as principal component analysis (PCA) to reduce dimensionality and collinearity.

- **Model testing**: Re-estimating the model with one of the collinear variables dropped (either **loginf** or **logrem**) could help clarify the impact of multicollinearity on our results.

In the presence of moderate multicollinearity as indicated by these diagnostics, it's still technically possible to conduct Forecast-error Variance Decomposition (FEVD) and Impulse Response Functions (IRF) analyses. However, there are some important considerations and limitations to keep in mind:

Precision and stability: Multicollinearity can affect the precision of the estimated coefficients in our model. This imprecision can carry over into our FEVD and IRF analyses, potentially leading to less reliable or stable results.

Confidence intervals: The standard errors of the estimated coefficients are likely to be inflated due to multicollinearity, which might result in wider confidence intervals for the IRF estimates.

Interpretation difficulties: The interpretation of the results from FEVD and IRF analyses could be complicated by the fact that the independent variables (in our case, **loginf** and **logrem**) are not entirely independent. Changes in one variable may be indistinguishable from changes in the other, which can cloud interpretations of causal pathways and impacts.

Forecast-error variance decomposition (FEVD)

Table 3.34

Forecast-error variance decomposition (FEVD), Sub-Saharan Africa and MENA region

Response variable and Forecast horizon			Impulse variable		
			LogRem	LogInformal	PS
	LogRem	0	0	0	0
		1	1	0	0
		2	0.9998292	0.0000289	0.0001419
		3	0.9994764	0.0000895	0.000434
		4	0.9989845	0.0001752	0.0008403
		5	0.9983889	0.0002804	0.0013308
		6	0.9977189	0.0004004	0.0018807
		7	0.996999	0.0005313	0.0024698
		8	0.9962487	0.0006696	0.0030817
		9	0.9954841	0.0008127	0.0037033
		10	0.9947177	0.0009582	0.0043241
	LogInformal	0	0	0	0
		1	0.0270135	0.9729865	0
		2	0.0754016	0.9071817	0.0174167
		3	0.13863	0.8104666	0.0509034
		4	0.2067437	0.7023058	0.0909505
		5	0.2721521	0.5979086	0.1299393
		6	0.3308985	0.5054557	0.1636458
		7	0.3818425	0.4275312	0.1906264
		8	0.4253877	0.3635707	0.2110417
		9	0.4625482	0.311709	0.2257428
		10	0.4944437	0.2698015	0.2357548
	PS	0	0	0	0
		1	0.0055955	0.0130944	0.9813101
		2	0.0028248	0.0099614	0.9872138
		3	0.0034259	0.0076852	0.988889
		4	0.0066945	0.0060624	0.9872432
		5	0.012058	0.0049327	0.9830093
		6	0.0190546	0.0041712	0.9767742
		7	0.0273138	0.0036816	0.9690046
		8	0.0365386	0.0033899	0.9600715
		9	0.0464902	0.0032397	0.9502701
		10	0.056976	0.0031884	0.9398355

The table 23 shows a Forecast-error Variance Decomposition (FEVD) from a Panel Vector Autoregression (PVAR) model, analyzing the effects of shocks in one variable on the forecast error variance of other variables over different forecast horizons for the variables LogInformal, LogRem, and PS (political stability) in SSA and MENA regions. This analysis helps us understand how much of the future variation in each variable can be explained by its own shocks versus shocks to other variables in the system. Here are the findings for each response variable over different horizons:

FEVD for LogInformal

- Immediate Horizon (0): No variance is explained by any variable, which is typical at horizon 0 since no shocks have yet occurred.
- Short-term (Horizon 1): Variance in LogInformal is fully explained by its own shocks.
- Medium-term (Horizon 2-6): Gradually, shocks to LogRem and PS begin to explain more of the variance in LogInformal. The proportion explained by LogInformal's own shocks decreases over time from about 96.3% at horizon 2 to 60.6% at horizon 6.
- Long-term (Horizon 7-10): Shocks to LogRem and PS explain increasingly larger portions of the forecast error variance in LogInformal, indicating growing external influences over time. By horizon 10, LogRem and PS together explain approximately 43% of the variance in LogInformal.

FEVD for LogRem

- Immediate Horizon (0): Similar to LogInformal, no variance is explained by any variable at the immediate horizon.
- Short-term (Horizon 1): Almost all variance in LogRem is explained by its own shocks (97.3%).
- Medium to Long-term (Horizon 2-10): The influence of LogRem's own shocks remains dominant, only slightly decreasing to 95.9% by horizon 10. The contributions of shocks from LogInformal and PS remain minimal, though they slightly increase over time.

FEVD for PS

- Immediate Horizon (0): No variance is explained by any variable.
- Short-term (Horizon 1): The vast majority of variance in PS is explained by its own shocks (98.1%).

- Medium to Long-term (Horizon 2-10): Shocks to LogRem become increasingly important in explaining variance in PS, from a negligible 0.4% at horizon 2 to 5.7% at horizon 10. The variance explained by PS's own shocks gradually decreases but remains the dominant factor.

Interpretation in SSA and MENA contexts

This decomposition is crucial for understanding economic dynamics in the SSA and MENA regions:

- LogInformal: The increasing influence of LogRem and PS on LogInformal suggests that remittances and political stability are important factors in determining the size of the informal sector over time. This might reflect the dependence of informal economic activities on external financial inflows and the broader political environment.
- LogRem: The dominance of LogRem's own shocks in explaining its variance indicates that remittances are relatively stable and influenced mainly by their own past values rather than other factors like the size of the informal sector or political stability.
- PS: The decreasing influence of PS's own shocks and the increasing role of LogRem indicate that external economic factors (like remittances) gradually become more significant in influencing political stability.

These insights can guide policymakers in both regions to focus on stabilizing remittance flows and enhancing political stability as strategies to manage the informal sector and overall economic health.

Table 3.35

Forecast-error variance decomposition (FEVD), Latin America region

Response variable and Forecast horizon			Impulse variable		
			LogInformal	LogRem	PS
LogInformal		0	0	0	0
		1	1	0	0
		2	0.934952	0.0643565	0.0006915
		3	0.8965571	0.1020866	0.0013564
		4	0.8747457	0.1232966	0.0019577
		5	0.8610588	0.1364244	0.0025168
		6	0.8516851	0.1452714	0.0030435
		7	0.8448409	0.1516184	0.0035406
		8	0.8396071	0.1563841	0.0040089
		9	0.8354657	0.160086	0.0044483
		10	0.8321028	0.1630379	0.0048593
LogRem		0	0	0	0
		1	0.0002306	0.9997693	0
		2	0.0582453	0.9406003	0.0011544
		3	0.1189823	0.8791379	0.0018798
		4	0.1694974	0.8283619	0.0021407
		5	0. 2106487	0.7871931	0.0021582
		6	0.2445024	0.7534201	0.0020775
		7	0.2727095	0.7253146	0.0019759
		8	0.296482	0.7016271	0.0018909
		9	0.3167143	0.6814474	0.0018382
		10	0.3340793	0.6640989	0.0018218
PS		0	0	0	0
		1	0.0020048	0.0025549	0.9954404
		2	0.003952	0.0030837	0.9929643
		3	0.0060932	0.0029597	0.9909471
		4	0.0084838	0.0026922	0.988824
		5	0.0111225	0.0024519	0.9864256
		6	0.013979	0.0022983	0.9837227
		7	0.0170097	0.0022505	0.9807397
		8	0.0201665	0.00231	0.9775235
		9	0.0234006	0.0024696	0.9741298
		10	0.0266662	0.0027176	0.9706162

Interpretation of FEVD Results

- For logrem (Logarithm of Remittances):
  - Immediate Impact (Horizon 0): All of the forecast error variance of logrem is explained by its own shocks.
  - Short-Term (Horizon 1-2): Nearly all the variance in remittances is still explained by its own shocks, with a very small percentage explained by loginf.
  - Medium to Long-Term (Horizon 3-10): As the forecast horizon increases, the influence of loginf on logrem steadily increases, indicating that economic activities in the informal sector increasingly explain the variations in remittances over time. This could reflect a scenario where changes in the informal sector, perhaps due to economic policies or external economic conditions, start affecting the flow of remittances.

- For loginf (Logarithm of Informal Sector Size):
  - Immediate to Short-Term (Horizon 0-1): Almost all of the forecast error variance of loginf is explained by its own shocks initially.
  - Medium to Long-Term (Horizon 2-10): A gradual increase in the proportion of variance explained by logrem suggests a growing impact of remittances on the informal sector size over time. This could be due to remittances funding informal sector activities or affecting economic conditions that influence the informal sector.

- For ps (Political Stability):

  - Immediate to Short-Term (Horizon 0-1): The variance in political stability is overwhelmingly explained by its own shocks, indicating a high degree of autonomy in how political stability evolves over time.
  - Medium to Long-Term (Horizon 2-10): A gradual increase in the variance explained by loginf and logrem suggests that both the size of the informal sector and remittances start to have a more noticeable impact on political stability, albeit still small. This could be seen in how economic factors might influence political sentiments or stability indirectly.

Economic Implications for Latin America

- Impact of Informal Sector and Remittances: The results suggest a significant economic interplay between remittances and the informal sector in Latin America. As remittances increase, they might be boosting the informal sector, either through direct investments or by providing a financial safety net that supports informal economic activities.
- Political Stability Dynamics: The relative independence of political stability from economic variables (remittances and informal sector size) in the short term indicates that other factors (like governance, external political pressures, or historical context) might be more influential. However, the gradual increase in economic influences over time suggests that long-term political stability could be subtly shaped by economic conditions.
- These insights can be crucial for policymakers and economic planners in Latin America, emphasizing the importance of considering the broader economic impacts when designing policies related to remittances and the informal sector, as well as the potential for these economic factors to influence political stability over time.

Table 3.36

Forecast-error variance decomposition (FEVD), OECD region

Response variable and Forecast horizon			Impulse variable		
			LogInformal	LogRem	PS
	LogInformal	0	0	0	0
		1	1	0	0
		2	0.9763146	0.0191097	0.0045757
		3	0.928192	0.0557916	0.0160164
		4	0.8653089	0.1008749	0.0338162
		5	0.7967162	0.1468299	0.056454
		6	0.7290688	0.1888359	0.0820954
		7	0.6663591	0.2245626	0.1090783
		8	0.6104619	0.253419	0.136119
		9	0.5618644	0.2758067	0.1623289
		10	0.5202729	0.2925794	0.1871477
	LogRem	0	0	0	0
		1	0.0082166	0.9917834	0
		2	0.005863	0.9841817	0.0099553
		3	0.0043723	0.9670662	0.0285615
		4	0.0034959	0.9446308	0.0518733
		5	0.0030338	0.9199247	0.0770414
		6	0.0028363	0.8950301	0.1021337
		7	0.0027962	0.8712844	0.1259193
		8	0.0028404	0.8494837	0.147676
		9	0.0029209	0.8300407	0.1670384
		10	0.0030086	0.8131056	0.1838858
	PS	0	0	0	0
		1	0.0104699	0.0006255	0.9889045
		2	0.0091488	0.001594	0.9892572
		3	0.0080325	0.0054318	0.9865357
		4	0.0071697	0.0113083	0.981522
		5	0.0065861	0.0183945	0.9750194
		6	0.0062836	0.0259389	0.9677775
		7	0.0062426	0.0333255	0.9604319
		8	0.0064275	0.0401048	0.9534677
		9	0.0067932	0.045998	0.9472088
		10	0.0072908	0.0508788	0.9418305

Interpretation of FEVD

- **Loginf (Logarithm of the Informal Sector Size):**
    - Initially, the forecast error variance of loginf is solely due to its own shocks (1.0 or 100% at horizon 1).
    - Over time, the influence of its own shocks decreases, while the contributions from logrem (Logarithm of Remittances) and ps (Political Stability) gradually increase. By horizon 10, loginf's variance due to its own shocks has decreased to about 54.53%, with logrem and ps explaining around 12.29% and 33.18% of the variance, respectively.
- **Logrem (Logarithm of Remittances):**
    - For logrem, the variance is predominantly explained by its own shocks across all horizons, starting at 98.76% at horizon 1 and slightly decreasing to about 96.94% by horizon 10.
    - The impact of shocks to loginf and ps on logrem is minimal but slightly increases over the horizons, indicating a small but growing interconnectedness with these variables.
- **PS (Political Stability):**
    - The variance of ps is almost entirely due to its own shocks at horizon 1 (99.36%). However, this dominance gradually decreases over time.
    - By horizon 10, shocks to ps still explain a significant majority (about 84.83%) of its forecast error variance, but the influence of shocks to loginf and logrem increases, indicating that both the informal sector size and remittances begin to play a role in explaining the forecast variance of political stability.

Implications for Economic Policy and Analysis

- Sectorial Interdependence: These results highlight the interdependence between the informal sector, remittances, and political stability. Policies aimed at one area (e.g., increasing formalization of the informal sector or stabilizing political environments) will likely have spillover effects on the other variables.
- Importance of Remittances: The strong influence of remittances on its own variance suggests that remittances are a critical economic factor in OECD

countries, with a relatively independent path that is less affected by the informal sector and political stability initially.

- Stability and Response to Shocks: The results indicate that political stability is mostly influenced by its own innovations but is increasingly affected by economic factors over time. This suggests that efforts to enhance political stability might benefit from considering economic factors such as the size of the informal sector and remittance flows.

Table 3.37

Forecast-error variance decomposition (FEVD), OECD region, Remittances Paid

Response variable and Forecast horizon			Impulse variable		
			LogRem	LogInformal	PS
	LogRem	0	0	0	0
		1	1	0	0
		2	0.9810145	0.0180724	0.0009132
		3	0.9517386	0.0470208	0.0012407
		4	0.9207377	0.0781188	0.0011435
		5	0.8904969	0.108538	0.0009652
		6	0.8615031	0.1375027	0.0009942
		7	0.8337334	0.1647959	0.0014707
		8	0.8070793	0.1903287	0.002592
		9	0.7814491	0.2140384	0.0045125
		10	0.7567851	0.235873	0.0073419
	LogInformal	0	0	0	0
		1	0.0484798	0.9515203	0
		2	0.0407632	0.9539642	0.0052726
		3	0.0354473	0.9486228	0.01593
		4	0.0308437	0.938464	0.0306923
		5	0.0266723	0.9246339	0.0486938
		6	0.0229862	0.9078984	0.0691154
		7	0.0199007	0.8889199	0.0911794
		8	0.017514	0.8682984	0.1141875
		9	0.0158854	0.8465678	0.1375468
		10	0.0150334	0.8241898	0.1607768
	PS	0	0	0	0
		1	0.0033905	0.0000673	0.9965422
		2	0.0043232	0.0108132	0.9848637
		3	0.0087608	0.0173275	0.9739118
		4	0.0157239	0.0193287	0.9649474
		5	0.0242151	0.0190254	0.9567595
		6	0.0335221	0.0178606	0.9486174
		7	0.0431603	0.0165384	0.9403012
		8	0.0527972	0.0153463	0.9318566
		9	0.0622063	0.0143693	0.9234244
		10	0.0712388	0.0136052	0.9151561

Interpretation of FEVD

- **loginf (Log of the size of the informal sector)**
  - At horizon 0, **loginf** is solely responsible for its own forecast error variance, as expected.
  - Over time, while **loginf** continues to explain the majority of its forecast error variance (over 81.8% at horizon 10), the impact of **ps** (political stability) on the forecast error variance of **loginf** increases from nearly 0% to about 16.1% by the 10th period. This suggests that shocks to political stability increasingly affect the forecast error variance of the informal sector size as time progresses.
  - The impact of **logrempaid** (log of remittances paid) is relatively minor but grows to about 2% by the 10th period, indicating a small but increasing influence of migration-related financial flows on the informal sector.
- **logrempaid (Log of remittances paid)**
  - Initially, **logrempaid** mainly explains its own variance (95.2%) at horizon 1.
  - As the horizon extends, the influence of **loginf** on the forecast error variance of **logrempaid** grows significantly, accounting for 41.3% by the 10th period. This illustrates a substantial interdependence between the size of the informal sector and remittance flows, potentially indicating that changes in the informal sector significantly affect remittance behaviors over time.
  - **ps** has a very modest influence, increasing slightly to just over 0.8% by the 10th period.
- **ps (Political stability)**
  - Political stability is overwhelmingly determined by its own past values, with nearly 99.6% at horizon 1 and about 91.7% by the 10th period.
  - **loginf** and **logrempaid** together increase their explanatory power over the variance in **ps**, totaling approximately 8.1% by the 10th period. This indicates that economic factors, encapsulated by the informal sector size and remittances, gradually exert a growing influence on political stability.

Implications and Policy Insights

The FEVD results suggest that while each variable is primarily influenced by its own shocks in the short term, there is significant interplay among them as the forecast horizon extends. In particular:

- **Economic and Political Interactions**: The increasing influence of **loginf** and **logrempaid** on the variance of **ps** suggests that economic conditions and financial flows have a growing impact on political stability over time. This can be crucial for policy planning, indicating that economic interventions could have long-term political implications.

- **Migration and Informal Sector**: The strong impact of the informal sector on remittances over time implies that policies targeting economic formalization need to consider the potential impacts on migration patterns and remittance flows.

- **Policy Stability**: The dominant influence of past values of political stability on its own variance emphasizes the inherent inertia in political systems, suggesting that changes in political stability are gradual and heavily influenced by past conditions.

These findings are critical for policymakers, economists, and researchers focusing on the dynamics within OECD countries, providing a foundation for developing strategies that consider the temporal interdependencies among informal economic size, migration, and political stability.

Table 3.38

Forecast-error variance decomposition (FEVD), High Remittance-to-GDP Ratio Countries ($\frac{Rem}{GDP} > \mathbf{0.84}\%$)

Response variable and Forecast horizon			Impulse variable: LogInformal	Impulse variable: LogRem	Impulse variable: PS
	LogInformal	0	0	0	0
	LogInformal	1	1	0	0
	LogInformal	2	0.9631816	0.0353342	0.0014841
	LogInformal	3	0.9226218	0.0733567	0.0040215
	LogInformal	4	0.8898038	0.1031277	0.0070685
	LogInformal	5	0.8647301	0.1249165	0.0103534
	LogInformal	6	0.8455073	0.1407699	0.0137229
	LogInformal	7	0.8304608	0.1524606	0.0170786
	LogInformal	8	0.8184013	0.1612452	0.0203535
	LogInformal	9	0.8085266	0.1679726	0.0235008
	LogInformal	10	0.800297	0.1732141	0.026489
	LogRem	0	0	0	0
	LogRem	1	0.0318104	0.9681897	0
	LogRem	2	0.0640698	0.9359244	5.90e-06
	LogRem	3	0.0974688	0.9025193	0.0000119
	LogRem	4	0.1276555	0.8722493	0.0000952
	LogRem	5	0.1533246	0.846348	0.0003275
	LogRem	6	0.1746026	0.8246585	0.000739
	LogRem	7	0.1920813	0.8065951	0.0013236
	LogRem	8	0.206417	0.7915286	0.0020544
	LogRem	9	0.2181963	0.7789078	0.0028958
	LogRem	10	0.2279059	0.7682825	0.0038116
	PS	0	0	0	0
	PS	1	6.51e-06	0.0004577	0.9995358
	PS	2	0.0002461	0.0017234	0.9980305
	PS	3	0.000654	0.0035646	0.9957814
	PS	4	0.0011294	0.0049552	0.9939154
	PS	5	0.0016341	0.005835	0.9926309
	PS	6	0.0021507	0.0063368	0.9915124
	PS	7	0.0026695	0.0065931	0.9907373
	PS	8	0.003183	0.0067007	0.9901164
	PS	9	0.0036849	0.0067239	0.9895912
	PS	10	0.0041701	0.0067032	0.9891267

Interpretation of FEVD

loginf Forecast Error Variance

- **Immediate term (Horizon 0)**: No variance explained as the initial condition.
- **Short term (Horizon 1)**: 100% of the forecast error variance in **loginf** is explained by itself.
- **Medium to long term**: The contribution of **loginf** to its own forecast error variance decreases gradually, indicating increasing influence from the other variables, particularly **logrem**. By horizon 10, **loginf** explains about 80.03% of its own forecast variance, **logrem** contributes about 17.32%, and **ps** about 2.65%.

LogRem Forecast Error Variance

- **Immediate term (Horizon 0)**: Similarly, no variance explained at the outset.
- **Short term (Horizon 1)**: Nearly 97% of the variance in **logrem** is explained by itself, with a small contribution from **loginf**.
- **Medium to long term**: **logrem**'s own contribution to its forecast error variance decreases, though it remains predominant. By horizon 10, **logrem** accounts for about 76.83% of its own forecast error variance, **loginf** contributes about 22.79%, and **ps** about 0.38%.

Ps Forecast Error Variance

- **Immediate term (Horizon 0)**: Almost entirely explained by **ps** itself.
- **Short term to long term**: The variance in **ps** remains overwhelmingly explained by itself across all horizons, maintaining above 98.91% by horizon 10. The contributions from **loginf** and **logrem** remain marginal, indicating that **ps** is largely influenced by its own past values rather than by the other variables in the model.

Insights and implications

- **Dynamics and interdependencies**: The FEVD shows significant interdependencies between **loginf** and **logrem**, reflecting a substantial reciprocal influence. However, **ps** appears relatively isolated in terms of its error variance being influenced by the other variables, suggesting it might be driven by different factors not captured by **loginf** and **logrem**.

- **Policy and analysis considerations**: Understanding these dynamics can be crucial for policy formulation, especially in contexts where the informal sector and remittances play significant roles. It suggests that policies affecting one may have significant spillover effects on the other.

Recommendations for multicollinearity consideration

Despite the presence of multicollinearity between **loginf** and **logrem**, the FEVD analysis suggests meaningful dynamic interactions worth considering. However, it's important to acknowledge that multicollinearity could still affect the precision of the estimates. In terms of policy analysis and forecasting, it would be prudent to include robustness checks, possibly exploring scenarios with reduced multicollinearity to confirm the consistency of these interactions.

Impulse response factor (IRF) analysis

Figure 3.10

Impulse response factor (IRF), Sub-Saharan Africa and MENA region

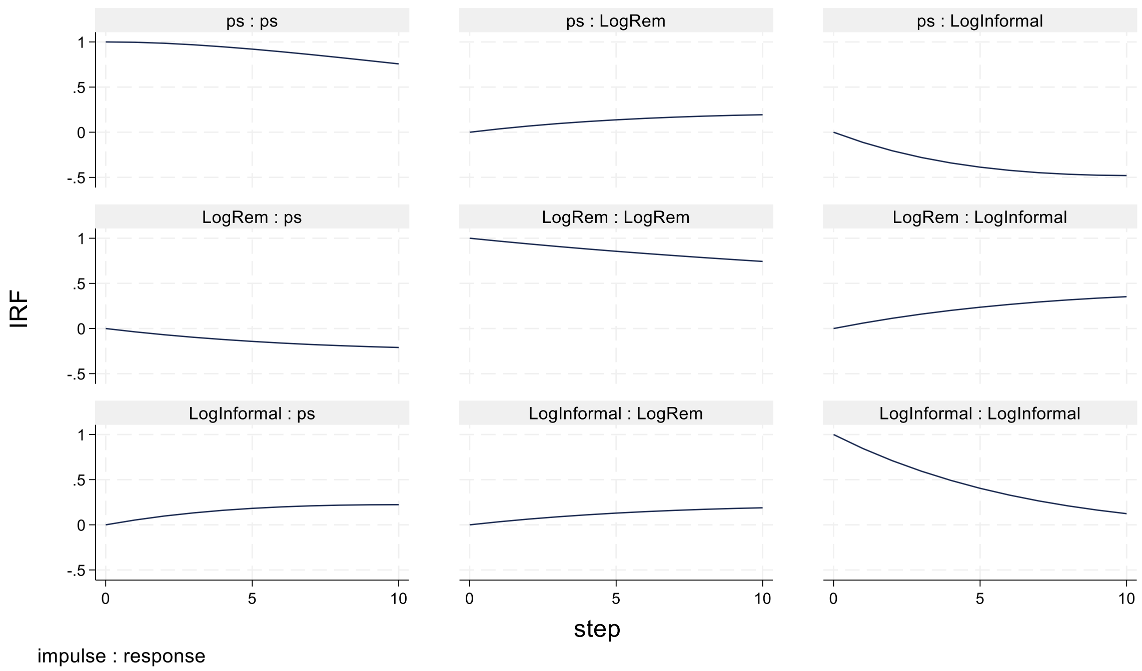


Figure 3.10 shows Impulse Response Function (IRF) graphs for the Sub-Saharan Africa and MENA region. Impulse Response Functions (IRFs) describe how one variable in a system responds to a shock or impulse in another variable over time. This is crucial in time-series analysis, particularly in Vector Autoregression (VAR) or Panel Vector Autoregression (PVAR) models, as it helps understand the dynamic effects of shocks across variables.

Given the dimensions and brief description, the IRFs seem to plot the response of each variable to shocks in each of the other variables across different time steps (0 to 10). Each row and column in the IRF plots likely represents:

- Columns (Impulse Variables): The source of the shock (e.g., PS, LogRem, LogInformal).
- Rows (Response Variables): The variables whose responses to the shocks are being measured (e.g., PS, LogRem, LogInformal).

Steps to Analyze the IRFs:

- Identify the Nature of Shocks: Determine what a positive or negative shock in each impulse variable represents (e.g., increase in political stability, increase in remittances).
- Observe the Response Patterns: Look at how each response variable's graph changes over time following a shock:
    - Immediate vs. Delayed Responses: Does the variable respond immediately, or is there a lag?
    - Direction of Response: Does the variable increase or decrease in response to a shock?
    - Duration and Decay: How long does the response last, and how quickly does it return to baseline or stabilize?
    - Inter-variable Dynamics: Understand the interactions between variables. For example, how does an increase in remittances affect political stability and the informal sector?

Panel Descriptions and Interpretations

- **PS Impulse Responses:**
    - **PS → PS:** Shows a decline in response over time, starting from 1, which suggests that the effect of a shock to political stability on itself diminishes gradually.
    - **LogRem → PS:** A negative response that diminishes over time, indicating that a positive shock in remittances initially decreases political stability, but the effect lessens as time progresses.
    - **LogInformal → PS:** A small, initially flat response that begins to increase slightly, suggesting a delayed and modest positive effect of shocks in the informal sector on political stability.
- **LogRem Impulse Responses:**
    - **PS → LogRem:** A negative response that gradually diminishes, indicating that a shock to political stability tends to reduce remittances initially, but this effect decreases over time.

  - **LogRem → LogRem:** Starts high and diminishes slightly, showing the persistence of shocks in remittances on themselves, though the impact slightly weakens.
  - **LogInformal → LogRem:** A slight increase over time, suggesting that a shock to the informal sector has a progressively positive influence on remittances.
- **LogInformal Impulse Responses:**
  - **PS → LogInformal:** A negative and somewhat constant response, indicating a consistent negative effect of shocks in political stability on the informal sector.
  - **LogRem → LogInformal:** A generally increasing response, suggesting that shocks in remittances have a growing positive effect on the informal sector size over time.
  - **LogInformal → LogInformal:** Starts at zero and decreases, showing that a shock to the informal sector size tends to reduce its size over time, possibly indicating self-correcting mechanisms within the sector.

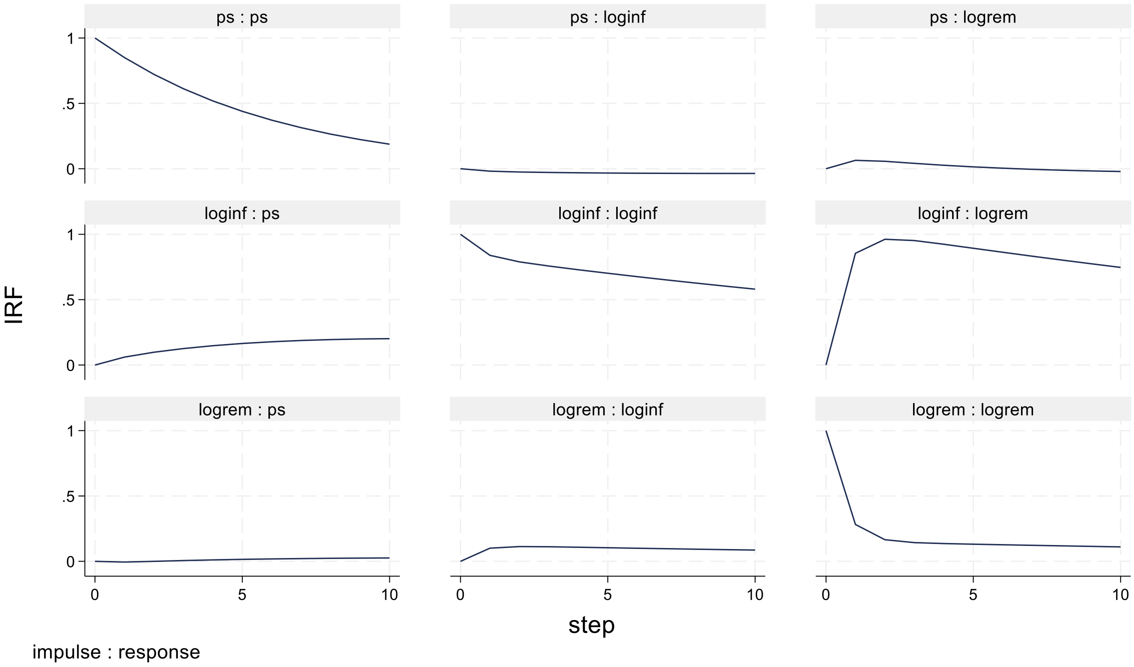
Insights for SSA and MENA Regions

- **Political Stability:** The negative initial responses of remittances and the informal sector to shocks in political stability highlight how instability might disrupt economic activities, though these effects diminish over time.
- **Remittances:** The increasing influence of the informal sector on remittances suggests potential feedback loops where growth in informal activities could encourage more remittances, possibly as remittances are used to support or expand these activities.
- **Informal Sector:** The different dynamics shown in response to shocks in PS and LogRem indicate the sector's sensitivity to changes in political and economic environments. A stable political climate might discourage reliance on the informal sector, while increased remittances might bolster it.

These IRF plots provide valuable insights into the interconnectedness of political, economic, and informal sector dynamics in the SSA and MENA regions. Policymakers could use this information to craft strategies that consider the implications of changes in one area on the others. For instance, stabilizing political conditions or facilitating remittance flows could have broader effects on economic stability and the size of the informal sector.

Figure 3.11

Impulse response factor (IRF), Latin America region



Graph Analysis: loginf to a Shock in logrem

- **Immediate response (Step 0 to Step 1):** The graph shows a significant initial rise in the response of the informal sector size (**loginf**) to a shock in remittances (**logrem**). This implies that remittances have a strong, immediate stimulative effect on the informal sector.

- **Short-term response (Step 1 to around Step 5):** After the initial sharp increase, the response slightly plateaus or slightly declines but remains substantially above the baseline. This pattern indicates that while the most substantial impact is immediate, the effect of the shock persists over time, maintaining a higher level than the initial state.

- **Long-term response (Step 5 to Step 10):** As the forecast horizon extends, the response gradually begins to taper but remains elevated relative to the baseline throughout the observed period. This suggests a lasting impact of the initial remittance shock on the informal sector, albeit with a decreasing influence as time progresses.

Economic interpretation

- **Immediate economic boost:**

The significant initial rise could be interpreted as an influx of remittances quickly being absorbed into the informal sector, possibly because these funds are used to support or expand small-scale, informal businesses or compensate for a lack of formal employment opportunities. This is particularly plausible in Latin American contexts where formal job markets may not be sufficient to absorb all labor force participants.

- **Sustained higher activity in the Informal Sector:**

- The sustained, albeit slowly decreasing, higher level of the informal sector size after a remittance shock might indicate that these financial inflows contribute to a medium-term expansion or support of informal economic activities. This could involve informal businesses scaling up or more individuals entering the informal economy as a reaction to increased availability of capital through remittances.
- **Long-term economic adjustments:**

The gradual decrease in the level of response over time, though still above the baseline, suggests that the informal sector gradually adjusts to the new economic conditions brought about by the remittance inflow. This adjustment might be due to the normalization of remittance flows or increased economic integration and formalization stimulated by initial remittance-driven growth.

Policy implications

- **Support for formalization efforts:** Policymakers might consider how to channel remittance inflows into more formal economic sectors or use them to stimulate formal employment creation, given their evident potential to boost economic activity.

- **Economic development strategies:** Understanding the strong link between remittances and the informal sector can guide the development of tailored economic development strategies that leverage remittances for broader economic benefits, such as through microfinance initiatives or small business support programs that encourage formalization.

- **Social protection and economic stability:** Ensuring that the informal sector, buoyed by remittances, can contribute to stable economic growth and development might require integrated policy approaches that address both remittance management and informal sector regulation.

This interpretation helps underline the significant role remittances play in influencing the size and scope of the informal sector in economies heavily reliant on these financial inflows, particularly in regions like Latin America where both remittances and informal economic activities are pivotal to the livelihoods of many.

Graph analysis: logrem to a Shock in loginf

- **Immediate response (Step 0 to Step 1):** The graph shows an abrupt and substantial increase in the response of remittances (**logrem**) to an initial shock in the informal sector size (**loginf**). This suggests a strong immediate sensitivity of remittance flows to changes in the informal sector.
- **Short-term response (Step 1 to around Step 5):** Following the initial sharp rise, the response of remittances quickly stabilizes and begins a gradual decline, though it remains considerably elevated above the baseline. This pattern indicates that while the initial reaction is strong, the impact of the shock begins to dissipate over time, yet it has a lasting effect that extends through the short-term period.
- **Long-term response (Step 5 to Step 10):** Over the longer term, the graph shows that the response of remittances slowly continues to decline, approaching but not completely returning to the baseline. This indicates a prolonged impact of the initial shock, although its influence diminishes progressively.

Economic interpretation

- **Immediate and strong reaction:**
    - The significant initial rise in remittances following a shock to the informal sector size could be interpreted as a compensatory mechanism. For instance, an increase in the informal sector might reflect economic distress or inadequate formal employment opportunities, prompting the diaspora to

increase remittances to support family members involved in or affected by the informal economy.

- **Gradual normalization with sustained effects:**
  - The gradual decline in the response over time suggests that the need for elevated remittance levels decreases as the situation stabilizes or as the initial shock's effects become fully absorbed and managed within the local economy. However, the fact that remittances do not completely revert to baseline levels within the observed period indicates a lasting change in remittance behavior.
- **Long-term adjustments :**
  - The sustained, though decreasing, level of response over the long term suggests that changes in the informal sector have a durable impact on remittance behaviors. This could be due to structural changes in the economy, lasting economic challenges, or a reevaluation by the diaspora of the economic needs of their families back home.

Policy implications

- **Economic policy and planning:** Understanding that remittances are responsive to the size of the informal sector can help policymakers develop strategies that either support the formalization of the economy or provide better support mechanisms for those who rely on the informal sector. Such strategies could potentially stabilize remittance flows.
- **Support for migrant families:** Policies aimed at supporting families that rely heavily on remittances could consider the implications of the informal sector's dynamics. Enhancing economic opportunities within the formal sector might reduce the dependence on remittances, leading to more sustainable economic development.

This analysis highlights the interconnectedness of remittances with the informal sector, reflecting how economic conditions directly influence financial support behaviors among migrant communities. This insight is particularly valuable for Latin American countries where both remittances and the informal sector play significant roles in the national economy.

Graph Analysis: logrem to a shock in ps

- **Immediate response (Step 0 to Step 1):** There appears to be a small immediate increase in the response of remittances to a shock in political stability. This suggests that any immediate reaction to changes in political stability is relatively quick, with remittances slightly increasing.
- **Short-term response (Step 1 to Step 5):** The response appears stable and maintains a slight elevation compared to the baseline. This implies that remittances consistently respond to an initial shock in political stability but do not continue to increase or decrease sharply; rather, they stabilize at a slightly higher level.
- **Long-term response (Step 5 to Step 10):** Over the longer term, the response continues to remain slightly above the baseline, suggesting a prolonged effect of the initial shock on remittances, although the effect size is modest.

Economic Interpretation

- **Immediate reaction and adjustment:**
  - The initial slight increase in remittances following a shock in political stability could indicate that migrants or the diaspora respond quickly to perceived threats or improvements in their home country's political landscape. This might be seen as a protective or supportive measure, sending more funds home either to help their families weather uncertainty or to take advantage of stabilizing conditions.
- **Sustained moderate response:**
  - The sustained yet moderate level of response suggests that while remittances are sensitive to changes in political stability, they do not fluctuate wildly in response to these changes. This could be because while political stability is an important factor influencing remittance flows, other factors such as economic conditions, exchange rates, and personal circumstances of the migrants also play crucial roles.

- **Long-term implications:**
    - The fact that the response levels off but remains above the baseline throughout the 10 steps might indicate a long-term adjustment in the remittance behavior of individuals influenced by the initial political shock. This could reflect a new equilibrium in remittance behavior—possibly a new, slightly higher level of remittances as a regular occurrence, influenced by the continuing perceptions of political stability or instability.

Policy implications

- **Remittance dependence:** Given that remittances show a response to political stability, policymakers should consider the implications of political decisions and stability on economic inflows from abroad, which can be significant for many families and even national economies in Latin America.

- **Support mechanisms:** Enhancing political stability might be used as a strategy not just for improving domestic conditions but also as a way to stabilize and possibly increase economic support from abroad through remittances.

This interpretation relies on the assumption that the shocks are unidirectional (from **ps** to **logrem**) and that other external factors are held constant. This analysis helps in understanding the dynamics of how political changes can affect economic behaviors such as remittance flows within the Latin American context.

Graph analysis: loginf to a shock in ps

From the IRF graph:

- **Immediate response (Step 0 to Step 1):** The graph shows a slight initial increase in the informal sector size in response to a shock in political stability. This suggests that political stability has a positive, though modest, immediate impact on the informal sector.

- **Short-Term response (Step 1 to around Step 5):** The response flattens somewhat after the initial increase, indicating that the immediate effects stabilize quickly. The informal sector size remains slightly above the baseline, suggesting a sustained, though not strong, effect of the initial shock.

- **Long-Term response (Step 5 to Step 10):** The response continues to plateau at this slightly elevated level without significant further changes. This stability indicates that the effects of the initial shock have a durable but steady impact on the informal sector over the observed period.

Economic Interpretation

- **Subtle positive influence:**
  - The slight initial rise in the informal sector size following a positive shock in political stability could suggest that greater stability makes informal sector activities either more viable or necessary. This might occur if, for instance, improved political stability leads to better overall economic conditions or if a stable political environment enables more predictable informal transactions.
- **Stabilization of the Informal Sector:**
  - The fact that the increase stabilizes quickly and does not continue to rise or fall dramatically could imply that the informal sector quickly adjusts to the new level of political stability. This could be due to the sector reaching a new equilibrium where the benefits of increased stability, such as reduced uncertainty and possibly improved law enforcement, have been fully realized.
- **Long-Term steady impact:**
  - The prolonged steady state of the informal sector size above the baseline suggests that the effects of improved political stability are enduring but do not progressively transform the sector. This could reflect a scenario where political stability has a foundational but limited role in influencing informal sector dynamics, possibly due to the resilience or inherent characteristics of the informal economy that make it less responsive to political changes beyond initial adjustments.

Policy Implications

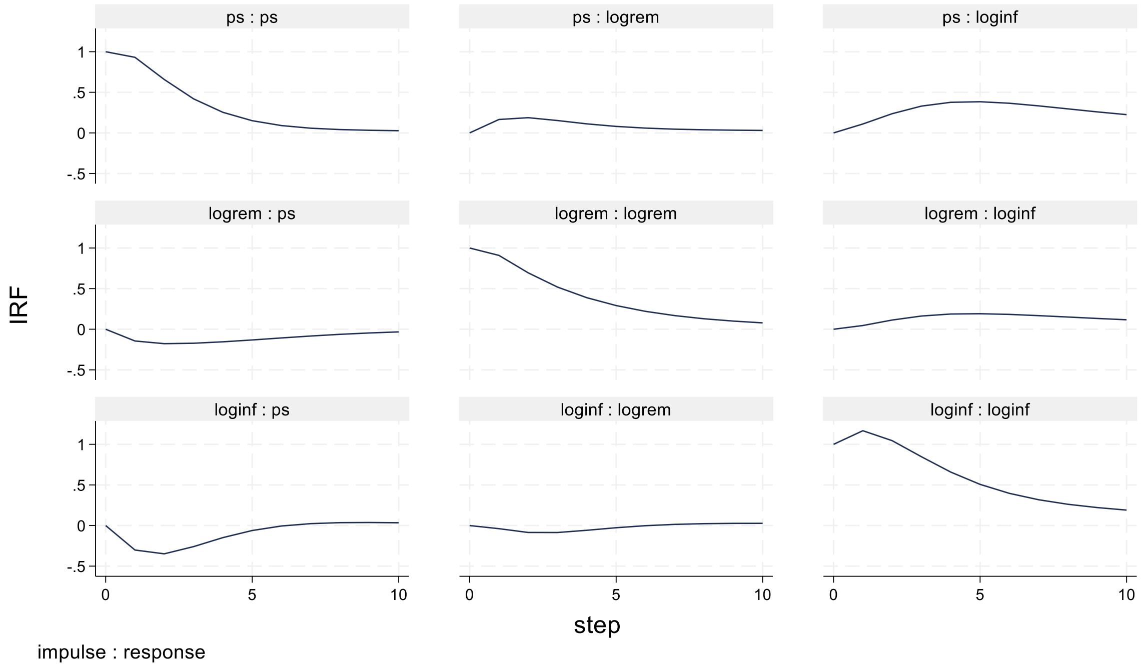
- **Policy Design and implementation:** The modest impact of political stability on the informal sector suggests that while efforts to improve political stability are certainly beneficial, they might need to be complemented with specific policies targeting the informal sector to significantly alter its size. This might include measures to encourage formalization, provide legal and financial support to informal businesses, or improve the regulatory environment to reduce barriers to formal sector entry.

- **Monitoring and evaluation:** Policymakers should continue to monitor the relationship between political stability and the informal sector, considering that stability alone does not drastically change the sector's size. Understanding this dynamic can help in designing more targeted interventions that address specific needs and opportunities within the informal economy.
- **Supportive infrastructure:** Improvements in political stability should be leveraged to build infrastructure and support systems that help integrate the informal sector more effectively into the formal economy. This can lead to more sustainable economic growth and reduced vulnerability of those working within the informal sector.

This analysis highlights that while political stability has a positive impact on the informal sector, the effect is moderate and stabilizes quickly, suggesting that other factors also play significant roles in shaping the sector's dynamics.

Figure 3.12

Impulse response factor (IRF), OECD region



Impulse Response Analysis

- **PS Response to various shocks:**

    - **PS to PS shock:** The response is initially positive and decays towards zero, indicating that political stability tends to gradually return to its equilibrium after a shock.

    - **PS to Logrem shock:** Shows a flat response close to zero, suggesting that shocks in remittances have minimal immediate or long-term impact on political stability.

    - **PS to Loginf shock:** Also near zero across the horizon, implying that shocks in the informal sector size similarly have little impact on political stability.

- **Logrem Response to various shocks:**

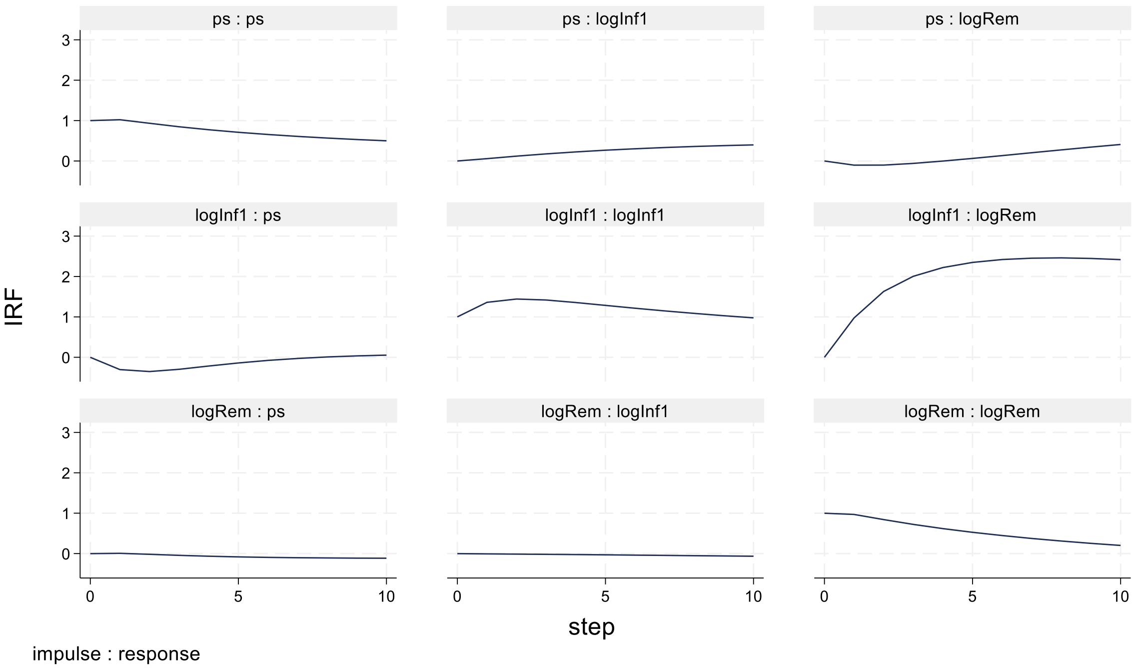
    - **Logrem to PS shock:** Indicates a slight negative response, turning neutral over time. This suggests a weak inverse relationship where increases in political stability may slightly depress remittances initially.

- **Logrem to Logrem shock:** The response is negative and diminishes over time, indicating that a shock in remittances leads to an initial reduction but stabilizes over time.
- **Logrem to Loginf shock:** Shows minimal response, implying that changes in the informal sector size do not significantly affect remittances.

- **Loginf response to various shocks:**
  - **Loginf to PS shock:** Displays a very slight negative response before stabilizing, suggesting a negligible impact of political stability shocks on the informal sector size.
  - **Loginf to Logrem shock:** The response is almost neutral throughout, indicating that remittances do not significantly affect the informal sector size.
  - **Loginf to Loginf shock:** Begins with a negative response and gradually approaches a less negative value, suggesting a damping effect where the informal sector may initially contract after a shock but recovers slightly thereafter.
- **Limited interdependence:** The overall minimal cross-variable responses suggest that each of these economic and political variables is somewhat insulated from shocks in the others within the time frame analyzed. This could imply either a strong internal equilibrium mechanism within each variable or that other external factors not included in this model are playing a significant role.
- **Economic stability:** The stability observed in responses, particularly for political stability and remittances, could reflect underlying resilience or robustness in these systems. This might be due to strong institutional frameworks in OECD countries that buffer against internal shocks.

Figure 3.13

Impulse response factor (IRF), OECD region, Remittances Paid



Analysis of Impulse Response Functions (IRFs)

- **ps : ps**:
  - A shock to political stability (**ps**) results in an immediate and relatively strong response in itself, which decays gradually over time. This suggests that political stability is primarily self-driven but does stabilize back to equilibrium slowly.
- **ps : logrempaid**:
  - A shock to remittances (**logrempaid**) has a minimal initial impact on political stability, which appears to increase slightly over time. This indicates a delayed and growing effect of remittance flows on political stability.
- **ps : loginf**:

- A shock to the informal sector size (**loginf**) has almost no immediate or long-term impact on political stability. This suggests that changes in the informal sector do not significantly affect political stability.

- **logrempaid : ps**:
  - Political stability shocks have negligible impacts on remittances, as shown by the flat IRF. This suggests that political stability does not significantly influence remittance behaviors.
- **logrempaid : logrempaid**:
  - Remittances are highly responsive to their own shocks, demonstrating an immediate strong response that decays slightly but remains quite influential over time. This indicates that remittance flows are self-sustaining and persistently influenced by their own past values.
- **logrempaid : loginf**:
  - A shock to the informal sector size has a very minor influence on remittances, which seems to remain consistent over the forecast horizon.
- **loginf : ps**:
  - Shocks to political stability have a very slight impact on the informal sector, which remains fairly constant throughout the periods. This implies limited influence of political conditions on the informal sector.
- **loginf : logrempaid**:
  - The response of the informal sector to shocks in remittances starts minimal and grows considerably over time, peaking at around period 10. This suggests a cumulative and increasing impact of remittance flows on the informal sector, possibly as migrant are absorbed into the economy and contribute mostly to informal activities.
- **loginf : loginf**:

- The informal sector shows a strong response to its own shocks, which stabilizes slightly but remains fairly constant. This reflects the self-driven nature of the informal sector and its persistence over time.

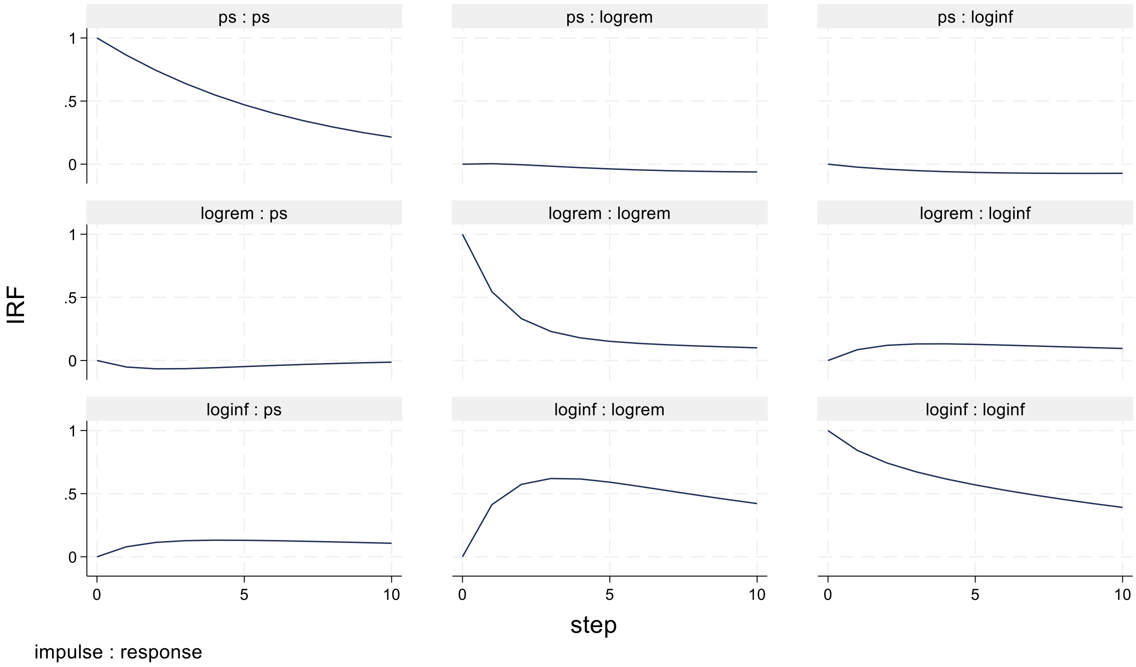
Summary and implications

- **Self-driven dynamics**: Each variable primarily responds to its own shocks, indicating that each is driven by internal dynamics.
- **Cross-variable influence**: There is a noticeable impact of remittances on the informal sector, suggesting economic ties between migration-related financial flows and informal economic activities.
- **Policy considerations**: The minimal cross-impact of political stability on economic variables suggests that policy measures aimed at political stability might not directly influence economic variables like the informal sector and remittances in the short term.

This detailed analysis of the dynamic responses can help policymakers and researchers understand the complex interrelationships between economic activities and political conditions within OECD countries, guiding targeted interventions and policy formulation.

Figure 3.14

Impulse response factor (IRF), High Remittance-to-GDP Ratio Countries ($\frac{\boldsymbol{Rem}}{\boldsymbol{GDP}} >$ $\mathbf{0.84\%}$*)*



Plot Analysis

Row 1: Responses to shocks in ps

- **ps to ps (ps : ps)**: A shock in **ps** shows a decreasing impact on itself over time, indicating that its influence diminishes gradually.

- **ps to logrem (ps : logrem)**: A shock in **ps** appears to have a negligible and stable effect on **logrem**, suggesting little to no dynamic influence.

- **ps to loginf (ps : loginf)**: Similarly, a shock in **ps** has minimal impact on **loginf**, reinforcing the notion of political stability being largely independent of changes in the informal sector size.

Row 2: Responses to shocks in logrem

- **logrem to ps (logrem : ps)**: The response of **ps** to a shock in **logrem** is minimal, consistent with the FEVD results showing that **ps** is primarily influenced by its own shocks.

- **logrem to logrem (logrem : logrem)**: A shock in **logrem** has a significant and decaying impact on itself, indicating persistence but diminishing over time.
- **logrem to loginf (logrem : loginf)**: The effect of a shock in **logrem** on **loginf** is noticeable and also decreases over time, reflecting a transfer of economic impacts from remittances to the informal sector.

Row 3: Responses to Shocks in loginf

- **loginf to ps (loginf : ps)**: A shock in **loginf** has a very slight impact on **ps**, consistent with the earlier observations of political stability's independence.
- **loginf to logrem (loginf : logrem)**: The response of **logrem** to a shock in **loginf** decreases slightly over time, suggesting some economic interactions but relatively moderate.
- **loginf to loginf (loginf : loginf)**: Shocks in **loginf** show strong self-persistence with a decaying impact, indicating that changes in the informal sector can sustain themselves over time but diminish.

Key Insights

- **Independence of Political Stability**: **ps** is largely unaffected by shocks in economic variables (**loginf** and **logrem**), highlighting its stability and perhaps different driving factors not captured by the other two variables.
- **Economic interdependence**: There's a significant interaction between **loginf** and **logrem**. Shocks in remittances (**logrem**) have visible impacts on the informal sector size (**loginf**), and vice versa. This suggests that policies affecting one may have ramifications for the other.
- **Time decay in responses**: Most IRF plots show a decay in impact over time, typical in economic systems where initial shocks are absorbed or mitigated through various economic or institutional adjustments.

Considerations for multicollinearity

Although the IRFs provide useful insights, the underlying multicollinearity between **loginf** and **logrem** suggests caution in interpretation. The precision of these estimates could be compromised, meaning that while the trends and directions of influence might be clear, the exact magnitudes should be interpreted with some skepticism.

Overall, these IRFs are valuable for understanding the dynamic interplay among the variables in our model, especially for policy-making and economic forecasting in contexts heavily influenced by remittances and the informal sector.

Variables definitions and sources

Variable	Code	Définition	Source
Net official development assistance and official aid received (current US$)	DT.ODA.ALLD.C D	Net official development assistance (ODA) consists of disbursements of loans made on concessional terms (net of repayments of principal) and grants by official agencies of the members of the Development Assistance Committee (DAC), by multilateral institutions, and by non-DAC countries to promote economic development and welfare in countries and territories in the DAC list of ODA recipients. It includes loans with a grant element of at least 25 percent (calculated at a rate of discount of 10 percent). Net official aid refers to aid flows (net of repayments) from official donors to countries and territories in part II of the DAC list of recipients: more advanced countries of Central and Eastern Europe, the countries of the former Soviet Union, and certain advanced developing countries and territories. Official aid is provided under terms and conditions similar to those for ODA. Part II of the DAC List was abolished in 2005. The	Development Assistance Committee of the Organization for Economic Co-operation and Development, Geographical Distribution of Financial Flows to Developing Countries, Development Co-operation Report, and International Development Statistics database. Data are available online at: www.oecd.org/dac/stats/idsonline.

		collection of data on official aid and other resource flows to Part II countries ended with 2004 data. Data are in current U.S. dollars.	
Net Migration	SM.POP.NETM	Net migration is the net total of migrants during the period, that is, the total number of immigrants less the annual number of emigrants, including both citizens and noncitizens. Data are five-year estimates.	United Nations Population Division. World Population Prospects: 2017 Revision.
Foreign direct investment, net inflows (BoP, current US$)	BX.KLT.DINV.CD.WD	Foreign direct investment refers to direct investment equity flows in the reporting economy. It is the sum of equity capital, reinvestment of earnings, and other capital. Direct investment is a category of cross-border investment associated with a resident in one economy having control or a significant degree of influence on the management of an enterprise that is resident in another economy. Ownership of 10 percent or more of the ordinary shares of voting stock is the criterion for determining the existence of a direct investment relationship. Data are in current U.S. dollars.	International Monetary Fund, Balance of Payments database, supplemented by data from the United Nations Conference on Trade and Development and official national sources.

GDP (current US$)	NY.GDP.MKTP.CD	GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in current U.S. dollars. Dollar figures for GDP are converted from domestic currencies using single year official exchange rates. For a few countries where the official exchange rate does not reflect the rate effectively applied to actual foreign exchange transactions, an alternative conversion factor is used.	World Bank national accounts data, and OECD National Accounts data files.
Personal remittances, received (current US$)	BX.TRF.PWKR.CD.DT	Personal remittances comprise personal transfers and compensation of employees. Personal transfers consist of all current transfers in cash or in kind made or received by resident households to or from nonresident households. Personal transfers thus include all current transfers between resident and nonresident individuals. Compensation of employees refers to the income of border, seasonal, and other	World Bank staff estimates based on IMF balance of payments data.

		short-term workers who are employed in an economy where they are not resident and of residents employed by nonresident entities. Data are the sum of two items defined in the sixth edition of the IMF's Balance of Payments Manual: personal transfers and compensation of employees. Data are in current U.S. dollars.	
Control of Corruption: Estimate	CC.EST	Control of Corruption captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.	Detailed documentation of the WGI, interactive tools for exploring the data, and full access to the underlying source data available at www.govindicators.org.The WGI are produced by Daniel Kaufmann (Natural Resource Governance Institute and Brookings Institution) and Aart Kraay (World Bank Development Research Group).
Political Stability and Absence of Violence/Terr	PV.EST	Political Stability and Absence of Violence/Terrorism measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism. Estimate gives the country's score on the aggregate indicator,	Detailed documentation of the WGI, interactive tools for exploring the data, and full access to the underlying source data available at www.govindicators.org.

orism: Estimate		in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.	
Voice and Accountability: Estimate	VA.EST	Voice and Accountability captures perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.	Detailed documentation of the WGI, interactive tools for exploring the data, and full access to the underlying source data available at www.govindicators.org.
Rule of Law: Estimate	RL.EST	Rule of Law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.	Detailed documentation of the WGI, interactive tools for exploring the data, and full access to the underlying source data available at www.govindicators.org.