Université Panthéon - Assas

École doctorale Sciences Économiques et Gestion

Thèse de doctorat en Sciences Economiques

soutenue le 11 Mars 2016

Marché et Réseaux : L'influence des liens interindividuels sur l'efficacité des échanges

Université Panthéon-Assas

Stéphanie Saba

Sous la direction de Annick Vignes

Directrice de Recherche, Ecole Nationale des Ponts et Chaussées

Rapporteur :

Richard Brooks : Professeur des Universités, Université de Yale, Etats-Unis

Stefano Demichelis : Professeur des Universités, Université de Pavia, Italie

Membres du jury :

Alan Kirman : Professeur Emérite, Directeur des études à EHESS, Université d'Aix-Marseille, France

Etienne Lehmann : Professeur des Universités, Université de Paris II, France

Thèse de doctorat Mars / 2016

Avertissement

L'université n'entend donner aucune approbation ni improbation aux opinions émises dans cette thèse ; ces opinions doivent être considérées comme propres à leur auteur.

Remerciements

Cette thèse ne serait jamais accompli sans votre présence et vos encouragements.

Tout d'abord, je tiens à remercier Madame Annick Vignes, ma directrice de thèse, d'avoir accepté de m'encadrer. Je tiens également à la remercier pour son soutien, son aide et sa présence depuis mon obtention du contrat doctoral et tout au long de mon trajet. Je lui suis reconnaissante pour ses encouragements à toutes les conférences auxquelles j'ai participé. Grâce à elle, j'ai eu la chance de rencontrer plein de personnes avec qui j'ai eu des échanges académiques extrêmement enrichissants.

Je tiens à remercier les membres de jury pour le temps qu'ils ont consacré à la lecture de mon travail. Je remercie les Professeurs Richard Brooks et Stefano Demichelis d'avoir accepté d'être rapporteurs, et les Professeurs Alan Kirman et Etienne Lehmann pour avoir accepté de faire partie des membres de jury.

Je tiens également à exprimer ma gratitude pour notre directeur du CRED Professeur Bruno Deffains, pour le vice président du Conseil d'Administration de l'Université Paris II Professeur Bertrand Crettez, et pour le président de l'Ecole Doctoral Professeur Sébastien Lotz. Je vous suis reconnaissante pour votre aide, votre support complet et votre présence à tout instant. Je souhaite remercier le Directeur Adjoint du CRED Professeur Etienne Lehmann pour sa présence sans failles au CRED, pour ses conseils et tout particulièrement pour son aide qui m'est très précieuse.

Mes remerciements sont doubles pour le Professeur Gilbert Faccarello. Je vous remercie d'avoir cru en moi. Merci pour votre appui moral, votre support et suivi continu pendant les années de thèse. Je suis très reconnaissante au Professeur Alain Pirotte pour son aide sans condition, son soutien moral permanent et son encouragement au sein du CRED.

Mes remerciements vont également au Professeur Damien Gaumont pour ces remarques et critiques sur mes slides et présentations, et pour la possibilité d'échange et de discussions sur mes travaux.

Je souhaite remercier Laura Hernandez pour l'attention particulière qu'elle a accordée à mon travail, ainsi que pour sa disponibilité complète depuis la conférence Wehia. Merci pour m'avoir introduit au monde des plantes et des pollinisateurs. Mon travail a considérablement bénéficié de son accompagnement et de ses conseils.

Je tiens à remercier tout particulièrement FranceAgrimer, pour l'apport et l'accès aux données sans lesquelles cette thèse n'aurait pu voir le jour.

Les TDs constituent une partie importante dans mon parcours. Je remercie les professeurs Gilbert Faccarello, Alain Pirotte, Damien Gaumont et Jean Mercenier de m'avoir accordé leur confiance dans l'enseignement de leurs matières. Je remercie également les chargés de TDs avec qui j'ai travaillé : Adrian et Thais.

L'ambiance de travail est aussi un facteur important dans l'aboutissement d'une thèse. Mes remerciements vont également aux représentants des institutions qui m'ont accueillies : l'ERMES, puis le CRED. Ces centres de recherche m'ont offert d'intéressantes opportunités et de bonnes conditions de travail. Sans oublier l'ensemble de mon laboratoire le CRED, je remercie Oliver Cardi, Christine Halmenschager, Micheal Visser, Claudine Desrieux, Fathi Fakhfakh et Professeur Gérard Ballot ainsi que les autres membres. Je tiens tout particulièrement à remercier nos chères secrétaires Naima et Josette pour leur sourire, disponibilité, assistance et organisation à tout instant.

Je remercie tous les doctorants du CRED, et particulièrement ma deuxième famille

"The CREDS" : Inaam, Aguibou, Farah, Jihan et Romain. Je vous remercie pour toutes ces années de Val de grâce, aux Fossés, à Assas et jusqu'à rue Valette. Merci votre support et votre présence ainsi que pour tous les moments passés ensemble : les rires, les conférences inoubliables, les weekends passés au bureau, les moments de bonne humeur ... Ces moments me tiennent énormément à coeur.
Je tiens à remercier aussi Nicolas, Manu et Emilio pour leur présence pendant toutes ces années, et les nouveaux doctorants : Tuan, Marie-Noelle et Hadi.

Un grand merci à Adelaide. Je suis maintenant sûre que l'amitié ne sera jamais "expliquée significativement" par la langue et le pays d'origine. Je te remercie infiniment pour tout.

Je tiens également à remercier Sylvain pour son aide et pour m'avoir introduit au monde de la modélisation et au monde des poissons, "le marché de Boulogne-sur-Mer".

Je souhaite remercier Christelle d'avoir relu toute ma thèse. Merci pour toutes les soirées passées par téléphone et par tout autre moyen de communication, afin de corriger la structure, la syntaxe et l'anglais. Merci de m'avoir soutenu et d'être toujours présente. Je remercie tous mes amis au Liban et en France spécialement les Omars. Merci de m'avoir supporté ces dernières périodes.

Mes remerciements sont plus personnelles à ma famille. Je ne saurai jamais les remercier suffisamment. Je remercie infiniment Grèce, Sabine, Julie, Bernard et Assaad. Je vous remercie pour votre présence et tous les encouragements. Merci de n'avoir jamais cessé de m'écouter, de m'épauler, de me comprendre, de me supporter, de m'aider et d'avoir subi mon stress.

Je remercie ma mère Fadia et mon père Saba pour leur appui, leurs prières et leur disponibilité sans failles. J'espère que vous êtes fières de moi.

Merci à Dory d'être toujours là et de m'avoir compris pendant ces derniers moments. Merci également pour ton attention très particulière et ta patience.

Un grand merci à S. Charbel.

Title and Abstract :

How to define and measure trust is still an enigma in economics, philosophy and sociology. This "three papers" thesis compares two different mechanisms - negotiated (decentralised submarket) and auction (centralised submarket) - on the basis of trust. Through an empirical study, the level of trust is evaluated and its impact is analysed on the "Boulogne-sur-Mer" fish market characterised by a stable coexistence of these two mechanisms. The three papers are preceded by a general introduction and a literature review. Paper one aims at comparing the nestedness and the robustness of both submarkets. Social network tools of ecologists are applied in order to provide an answer. Paper two models trust creation on both structures from the buyer side using the survival analysis and considering the buyer size. Paper three studies the effect of a trust index on the outcomes of transactions. Bipartite and projected graphs reveal the difference between submarkets. This thesis shows that the negotiated market is marked by a higher level of trust as agents interact and are not fully informed about the market situation unlike the auction one where information is centralised. We believe that trust is a way out of risk when there is lack of information.

Keywords :

Trust, social networks, auction, negotiated, market structure

Résumé :

La définition et la mesure de la confiance restent toujours une ambiguité en économie, sociologie et philosophie. Les "trois papiers" de cette thèse comparent, tout en considérant le niveau de confiance deux mécanismes de vente : la vente de gré à gré et la vente aux enchères. Le marché de Boulogne-sur-Mer, caractérisé par la coexistence stable de deux systèmes de vente constitue le centre de notre analyse empirique. Ces trois papiers sont précédés par une introduction générale et une revue de la littérature. Le premier papier est dédié à la comparaison des deux structures en termes de robustesse et de "nestedness", en s'appuyant sur de outils de réseaux employés par les écologistes. Le deuxième papier analyse la création des liens de confiance du côté de l'acheteur à l'aide d'un modèle de durée. La taille des acheteurs a son rôle sur la confiance. Le troisième papier s'intéresse à l'effet de l'indice de confiance sur les "outcomes" des transactions. Des graphes bipartis et homogènes montrent une différence de structure. Nos résultats affirment que le marché de gré à gré est plus atteint par la confiance comme l'information est décentralisée. Les agents se basent sur cette confiance comme alternative au risque. Cela n'est pas le cas des enchères où l'information est connue.

Descripteurs :

Confiance, structure du marché, enchères, négocié, réseaux sociaux

Sommaire

Introduction

North and others, tended to take some specific model of market organisation as given and then to examine the aggregate behaviour of the market (...) Frequently the individuals are thought of as acting independently of each other and linked only through the price system.(...) In fact it is clear that the situation is much more complicated than this. The organisation through which activities are coordinated is complicated and, for example, it is reflected in the networks that link people together.

Kirman (2010)

In the Pas-De-Calais district, situated in the north west region of France, is located the Boulogne-sur-Mer Fish Market. The Boulogne-sur-Mer city is not only known for being a principal fishing port in France, but also for creating a major link with England in the late twentieth century. It is the heart of connections, the most frequented meeting point for fishing areas and markets. Mostly French but also foreign boats (such as Netherlands and English boats) visit Boulogne-sur-Mer market [1]. The Boulogne-sur-Mer (BsM) fish market is the most important fish market in France in terms of quantity. More than five hundred tones of fish are sold daily on the dock. This market has its own particular organisation. Divided in two, the Boulogne-sur-Mer fish market is characterised by a stable coexistence of the two submarkets : an auction one and a negotiated one. Agents can freely choose where to sell and where to buy fish.

On the auction market (centralised market), it is hard to identify social interactions between agents and links are difficult to find. However, on the negotiated market (decentralised market), we believe that trust and network's creation are the keyword when seeking for goods. Agents are not fully informed about the market situation. Many articles tended to compare centralised and bilateral markets (Grossman & Stiglitz (1976), Milgrom (1986), Bulow & Klemperer (1996) , Blouin (2003) and Chong, Staropoli & Yvrande-Billon

1. The official site of the Boulogne-sur-Mer fish market : http ://www.portboulogne.com/fishing-port.html

(2014)). But till now there is no agreement on whether the centralised market or the decentralised one is the most efficient. Moreover this stable coexistence of the two designs is on itself an enigma. This thesis provides an explanation to this trade-off between the two mechanisms. Which market structure is more profitable to exchange goods, centralised or bilateral market ?

Since William Vickrey, the literature on centralised market has expanded at a fast rate. It seems that, for uninformed agents (buyers and sellers), centralised designs where information is common to all, are more efficient than decentralised designs, where information is hard to get. This idea has been proved in the 20th century with Milgrom (1986). In addition, the information availability in centralised and decentralised markets can influence agents behaviours. Unlike the auction market where information is already known, agents will look for credible signals in an imperfect market to obtain better prices and lower costs. Therefore, their past transactions on a negotiated market will influence the futur transactions. As Alesina & Ferrara (2002) said : "When people trust each other, transaction costs in economic activities are reduced, large organisations function better, governments are more efficient, financial development is faster : more trust may spur economic success". Since the 90's, a new literature has been developed using social network to underline agents behaviours. Social networks were then defined as networks composed of individuals constituting the nodes, which are linked by social interactions. The influence of social interactions on the functioning of markets will also be studied.

So why the Boulgone-sur-Mer fish market ?

The main goal of this thesis is to study the influence of trust on functioning of perishable good market and to show how the social network structure differs between the auction and the negotiated submarkets. The bonds between these trust links and asymmetry of information needs also to be analysed. Therefore, the Boulogne-sur-Mer french fish market was chosen. The fish market was the center of attention of economists (Graddy & Hall (2011) and Sapio, Kirman & Dosi (2011)) not only because fish is a perishable goods but also because the organisation of such markets varies and "they exhibit two features which make them a natural subject for economic analysis" (Gallegati, Giulioni, Kirman & Palestrini (2011*a*)). The main purpose of this thesis is to understand the coexistence of both market's structures and to compare them. Our goal is to be part of this debate by merging social network formation to market structure. We intend to prove that social links (as trust between buyer and seller) are more intense on the bilateral market where agents meet and interact. However, we believe that this is not the case when it comes to auction designs. But an important point should be indicated : trust can also prevail on centralised market even if the sellers are not present (comparing to bilateral markets). But how is that ? The seller (the boat) does not play a direct role on this market, therefore it is shown in this thesis that trust is somehow "different". On the centralised markets trust is linked to the name of the boat, while the latter has its own effect on decentralised markets. This thesis highlights this distinction.

On the Boulogne-sur-Mer fish market there are 80 different varieties of fish. The types of fish are the following : large or medium or small fish, alive or fresh or fish that has been caught for a moment. Retailers, resellers, restaurant owners and fish mongers have the choice to visit each day one or both submarkets. Buyers are constrained by time, volume and species they need to buy, and budgets. They have different elasticity of demand according to their identity ; for example an owner of an expensive restaurant is different than a retailer or an owner of a restaurant that only serve sandwiches and daily cheap platers. Fish is a perishable good that can not be managed by the fishermen who will find it hard to predict its supply. Its heterogeneity might explain the coexistence of the two designs. This high level of differentiation and the constraint lead to the non-identical and the wide variety of observed behaviour of buyers. Buyers and sellers on this fish market, as already mentioned, can either auction or negotiate. Buyers and sellers interact, bargain and have the possibility to create interpersonal links on decentralised market unlike the centralised one.

History :

Historically, from the Gall Roman period, through the Middle Ages, to the sixteenth and till the twentieth century, the Boulogne-sur-Mer fish market passed through several changes. After so many invasions by the vikings, the pirates and many others, the market has developed a trading relationship with England in the middle ages. Then, Henry VIII and Henry II did lots of works. Thus, this market has experienced a strong expansion period until it was destroyed during the second war, when the germans has occupied the port (98% of the port). After the war, and for a 10 year period, the port was reconstructed. From the late 80's, the Boulogne-sur-Mer fish market is occupying the leading fishing position in France [2].

The structure of the Boulogne-sur-Mer fish market has changed with time and this market had operated on a negotiated system for a long time. All the transactions were off auction from the year 2000 until 2005, when the organisers put in place the auction system [3] according to the U.E. instructions. However, the time constraints were high on this market and the tonnage were important, therefore it was impossible to sell all these quantities only on the auction submarket. That was the reason why buyers and sellers rejected this organisation and a double mechanism was introduced in April 2006, where both the auction and the negotiated systems coexisted. Nowadays, the Boulogne-sur-Mer fish market is known by this particular organisation that has attracted scholars attention.

The auction mechanism - where prices are more transparent - is used in order to accele-

2. The official site of the Boulogne-sur-Mer
3. Information throughout the interview with the responsible of the Boulogne-sur-Mer fish market

rate transactions whereas the negotiated submarket allows the buyers a better assessment of the quality of the fish.

The auction submarket opens at 4 a.m. and always operates at the same place. All the transactions are made through an electronic sale system. Its computerising was around the year 2008. Before that, the auction system was an ascending one on 7 charts at the same time where a crier directed the sales. This new protocol can be described by a descending price auction with a predetermined reserve price. *The fish is sold by a clock auction system and remotely on floating stock, on-line*[4]. The name of the boat, the type of the fish, the quantity and the price are displayed on the screen. Transactions on this submarket are anonymous and agents do not interact. We can describe this market as a quick market, where transactions occur at a fast rate, and buyers and sellers meet and interact on the negotiated submarket and bargain over prices simultaneously. The negotiated submarket is marked by its auto-organisation. On this submarket, the prices are not displayed and the bargaining process is resumed in a "take it or leave it price" strategy. This market is interesting because the amount of information differs between agents. Agents search for the best combination of price and quality. Therefore, relationships can be created between buyers and sellers.

Moreover, the quotas on the Boulogne-sur-Mer fish market are Europeans, allocated by countries according to the rules of relative stability. Its purpose is to encourage boats to catch one species and not to release fish back into the water. Fishermen choose their fishing areas. Year after year, the quantity of fish is decreasing due to overfishing, pollution and climate change. In the 80's, quotas were introduced to protect stocks and producers, which reduced production capacity.
Several adjustments took place following the entry of new countries. Quotas are now by species and by area of fishing. In France, the Organisation of Production (OP) allocates

4. The official site of the Boulogne-sur-Mer http ://www.portboulogne.com/fishing-port/the-fish-auction.html

the quotas. Fourteen production organisations in France are grouped into two federations : high-sea fishing and artisanal fishing. The Boulogne-sur-Mer fish market has two OP : "‘*FROM North*"’ (which includes the high-sea fishing) and the *CME (coopérative Maritimes Etaploises)* (which includes the artisanal fishing). The repartition of the quota is based on the prior capture of the ships. In other words, to fix the quota for the coming years, the past years fishing are taken in consideration. Rarely quotas are quotas by boat (only if the species are rare like the cod) and in this case, no resale for the quotas among fishermen is allowed. Generally, it is a collective distribution. Nowadays, quotas are increasing and somehow can be considered as a constraint therefore agents are encouraged to develop a strategy that reduces the constraint of the quotas.

How this fish market worked ?

This thesis studies the BsM fish market from April 2006 to December 2007 based on a FranceAgriMer database. This fish market known by its trading relationships contained 208 sellers and 100 buyers. Buyers and sellers met continuously on this market. It operated 6 days a week from 4a.m. till 8a.m. at the same place (for detailed descriptive statistics on the functioning of the Boulogne-sur-Mer fish market and in order to understand how a buyer and a seller spent a day on this market see appendix A.1) .

Each day, sellers had the possibility to choose on which submarket to trade. Once the submarket is chosen, most of them do not change their decision until the next day, while buyers can more freely go to both submarkets daily. The Boulogne-sur-Mer fish market has two sets of players : the ones who visit one submarket daily, and the ones who switch between submarkets. Ninety percent of the buyers moved at least one day between both structures. But the statistical tests showed that buyers do not have the same preference to both designs (See appendices B.3 and B.5). Taking into account the number of days they came to the BsM market, 65% of the buyers purchased daily on both submarkets half of the time. The buyers who came in a regular way to the BsM, are the ones who altered more between submarkets (See appendix B.1). While more than 50% of the sellers always vended their fish on only one submarket and never switched daily. The few ones who switched daily (See appendix B.2 and figure B.4), did not intend to divide their catching [5]. 88% of the sellers tried to sell daily on both submarkets at least once time. This action is not regularly repeated. Sellers cannot divide their fishes daily between submarkets because it is costly (see Mignot (2012)). Thus, once the market is chosen, it will be more beneficial if they do not change their decision until the next day. Sellers did not go to both submarket at the same frequency. Some of them had preferences to one submarket more than the other (appendix B.4).

Anyone can purchase fish at either negotiated or auction submarkets. Most of the clients are regular buyers but buyers-sellers relationships vary among submarkets. There are some buyers-sellers who have repeated encounters and others not. This thesis explores these distinctions between the two structures.

The Boulogne-sur-Mer fish market can also be introduced from a couple point of view. A pair of two different agents *i.e.* a seller and a buyer connected by a transaction is considered a couple. The situation can be presented as follows : each day, a seller and a buyer can (1) both or one of them be present on the same submarket the same day, (2) if both of them are present, they can meet or not on only one submarket the same day (possible couples), (3) if they meet, they can transact (formed couples) or not on the chosen submarket.

From April 2006 until December 2007, 11080 distinct couples were created, some of them could be differentiated by their particular partners and had stable relationship, and others were just nomadic couples. Some couples preferred to transact on the negotiated submarket while others on the auction or even on both submarkets. Whereas, some couples never traded.

5. Only 20% of the quantities are sold on the non-prior market. No relation can be noted between the switching daily fact in order to sell more.

The BsM database contains 208 sellers and 100 buyers. It is therefore possible to have 20 800 couples formed noting that not all of them will be present and will transact the same day on the BsM fish market. Hence, taking into account the agents presence on the market, 19087 couples may be formed over the period (possible couples), but only 11 080 couples transacted (formed couples). These 11 080 formed couples were present on both submarkets (10 125 on the negotiated, 7 842 on the auction and 6 887 on both submarkets [6]). Likewise each couple, present on a submarket, can transact or not. But where were the couples more present, on the auction or on the negotiated submarket ? On which submarket they had more repeated encounters ? Here in after, an answer to these questions will be given.

Some of the couples are indifferent where to meet, other prefer to meet on the auction while others only transact on the negotiated market. More couples intended to meet on the negotiated submarket (appendix B.6) where repeated encounters occur more often (appendix B.7). The auction submarket is marked by a higher number of couples created. But this is not related to the quantity exchanged on this submarket. 45.5% of the quantities are auctioned and no significant correlation can be reported between the couple creation and the quantity exchanged (See appendix B.8). This difference in the behaviour should be studied. Subsequently, this thesis will clarify it and will explain the effect of the market structure on the inter-individual links creation, and thus on the network formation.

The quantity, the price and the variety of the fish :

The BsM market is diversified in terms of quantity. Quantities varied tremendously. For example, 2 376 424.7 kilos were negotiated in November 2007 against 853 723 kilos in April 2006. In average, 1 162 000 kilos were negotiated monthly against 902 475 kilos that were auctioned. Important quantities of fish were sold in autumn (September, October and November) followed by spring and winter and the lowest quantities were in summer.

6. 11 080 = 10 125+ 7 842 - 6 887

During the whole period, Saturday was the big day during it 13 057 180 kilos were sold [7], followed by Friday and Wednesday (9 946 050 kilos and 9 329 026 kilos respectively). The lowest quantities were observed on Tuesday (4 562 606 kilos) and Thursday (4 254 690 kilos) and finally Monday (2 174 149 kilos). The market was closed on Sundays [8].

From April 2006 till December 2007, the number of fish varieties did not significantly vary according to the month. For the 21 months, 47 distinct types of fishes were exchanged in average each month on the auction submarket, (with a standard deviation of 2.55) and 50 types were negotiated (with a standard deviation of 2.78). The Boulogne-sur-Mer fish market was a highly diversified market when it comes to the variety of fish. We cannot find one species sold only on one submarket. Each species is auctioned and negotiated daily. The prices of these varieties can go from 0.1 euro per kilo to 42 euros per kilo. Fish are not sold at the same price on both submarket. Mignot (2012) divided these varieties into three categories : (1) the ones sold at higher price on auction and which represented 19 000 tons (52% of them were negotiated), (2) the ones that are sold significantly at a higher price on negotiated and which represented 4200 tons (74% of them were negotiated), (3) the ones that no significant difference can be noted among submarkets and which represented 20 000 tons of fish (56% of them were negotiated).
Besides, when it comes to rare fish, negotiation seems more worthwhile. These fish were sold at a higher price on the negotiated submarket than on the auction one ; when quantities decreased, sellers tended more to negotiate than to auction. The expensive species were negotiated.

Additionally, the fish that were sold at a higher price on the negotiated submarket were the ones that came from the small-scale fisheries. The small-scale fisheries are the maximum 18 meters boats that go in water for less than 24h. The fish that are auctioned at a higher price were caught by bigger boats (12 to 25 meters) that go twice a week in

7. from April 2006 till December 2007
8. 30% are sold on Saturday, 23% on Friday, 22% on Wednesday, 10% on Thursday and Tuesday and and 5% on Monday

water (between 24h and 48h). These boats are known by coastal fishing. To note that a negative relation was noted between the quantity exchanged and the prices at an aggregate level (see also Mignot (2012)).

The small-scale fisheries boats are most loyal to one market designs and hence do not switch the submarket from one day to another. Boats that tend to switch are the ones who negotiated less and auctioned more. So, these small boats tend to negotiate and the coastal fishing vessels are the most moveable. Boats can be divided into two categories : the ones who put their catching mainly on (1) auction and (2) negotiated. As for buyers, Mignot (2012) noted that this is not the case. Buyers identity is not revealed and no work are done concerning buyer's decision and behaviour.

In this thesis, taking into account the amount of information on each submarket, we will try to analyse the buyers choices and to understand the buyers behaviours and characteristics. Buyers behaviour can be related to the amount of information as it differs among submarkets. They intensify their relation with sellers on bilateral structure because information on this market is imperfect.

The main goal of this thesis is to study the influence of these intense relations - *"trust"*- on functioning of a perishable good market and to show how the social network structure differs between the auction and the negotiated submarkets. Relationship between these trust links and asymmetry of information needs also to be analysed.

Thesis outline

Chapter 1 : Quantifying the differences between the auction and the negotiated market : the role of the structure of interactions

It is commonly admitted among economists, that a market with a centralised structure (like an auction market) is more efficient than a decentralised one. The reason for this, being the fact that in the former, all the actors dispose of the same information while the negotiations remain private in the decentralised one. There is a large number of works comparing both types of market and recent studies start paying attention to the structure of the interactions (Vignes & Etienne (2011) and Bottazzi, Dosi & Rebesco (2005)). The Boulogne-Sur-Mer Fish Market, the most important one of France in terms of quantity, is an excellent case study to investigate this problem. This old market, which had operated in a decentralised way for long time, was led by UE regulations to adopt a centralised structure. However, this new way of functioning did not convince the economic actors and it was finally admitted, in 2006, to allow the two forms of market (auction and bilateral negotiation submarkets) to coexist in the same place. Detailed data concerning the daily transactions is available, allowing a comparison of the behaviour both submarkets under similar economic, seasonal, climatic and social conditions. In this work, we are interested in the structure of the social interactions that take place among the actors of both submarkets. These interactions can be described by the means of a complex network where the nodes are of two different kinds (representing buyers and sellers), and the links, that stand for the interactions, only connect nodes of different kinds. The network so obtained is bipartite. This network has weighted links when one takes into account the interactions of the whole period. We study this problem applying the tools and concepts commonly used to study ecological mutualist systems (Burgos, Ceva, Hernández & Perazzo (2009)). In these systems, the interactions between actors of two different guilds brings a mutual benefit to both, like in plant-pollinator, or plant-seed-dispersers networks. We investigate if there is some similar mechanism structures with the negotiated submarket where the actors come to know each other after a repeated number of visits and transactions. Our results show that the structures of the social interactions developed in both submarkets are different. In particular, we define an index that accounts for the "fidelity" of the interaction between the different couples of actors in both markets. The probability distribution of this fidelity index looks scale free in the negotiated market while it shows a sharper decrease in the auction one, suggesting that there is a threshold for the fidelity of the agents in the latter.

Chapter 2 : How long does it take a buyer to find his match ? Trust in duration model

There is a huge literature focusing on comparing both of centralised and decentralised structures. But till now, there is no consensus whether centralised designs are more or less efficient than decentralised ones. Here, our goal is not only to be part of an existing debate about the predominance of one design over the other but also to prove that the market structure plays an important role in the creation of intense bonds between buyers and sellers. Therefore duration models are tested : "Duration analysis is a core subject of econometrics" (den Berg (2000)). They are used for exemple in labor economics, strikes duration, marriage duration and duration until death (Kiefer (1988), Lillard (1993)). In this paper, the duration model studies the transition (the duration) from one state (searching state) to another (circle of trust).

To do so, the Boulogne-sur-Mer fish market marked by a stable coexistence of the centralised and the decentralised designs is analysed. Once on this market, buyers are searching for the best combination of price-quality. They can choose between either negotiating or auctioning. If auctioning is chosen, buyers have less risk as information is common to all. Whereas if they decide to negotiate, buyers will search for this information. After visiting the sellers on this submarket, buyers will (1) stay in the searching and the switching mode or (2) with time, they will get to know the sellers (the best combination of price-quality) and thus they choose the preferred ones. Consequently, buyers move from a searching mode and enter the circle of trust. They find a match.

Trust is not new in economics. It has been studied by Rosenberg (1956) then by Blau (1964) Putnam (1993) and Zak & Knack (2001) followed by Kirman & Vriend (2001), Alesina & Ferrara (2002), Dincer & Uslaner (2007) and Goyal (2009). But nowadays trust remains an unresolved problem. Nevertheless, trust has to be defined. An estimation for trust from the buyer side is done using the degree notion. And because we believe that trust can be related to buyers identity, this paper differentiates between buyers using four different variables : quantity, species, connected sellers and presence day. After a segmentation of buyers in order to better understand their behaviours, a model is created to define the probability of transition from one state to the other (searching state and trust state). Under a non-parametric model, survival and hazard curves are presented for each category of buyers, then under a parametric model, the buyers characteristics are considered.

Our results show that there is a link between the market structure and the creation of what we call "trust" as well as a link between the trust level and the buyer preference to a design. The duration analysis shows that the time transition from a state to another is related to the market designs and to the buyer preference and size. "Trustee" buyers, the small ones, intended to negotiate, while as the "zero trust" buyers (the big ones) are the one who auctioned more. Finally buyers who visit both designs at the same frequency, have different behaviour on each submarket when it comes to trust. When negotiating, they have a higher level of trust.

Chapter 3 : To trust or to bid : an empirical analysis of social relationships on a fish market

To trust or to bid gives an estimation to a trust index using probabilistic models. We estimate trust and analyse its importance through the study of this particular market. We show how the market design matters and how it influences trust.

First, after introducing the main feature and the data, an estimation of trust is done under a static framework. We calculate two probabilities : the probability that agents interacting randomly and the probability of interacting on the basis of past encounters. Repeated encounters are taken into account in our probabilities equations. Using these probabilities, we define a trust index. It puts in evidence the difference of the trust level on both submarkets. We test the difference between ratio's mean for both submarkets using the Satterthwaite test. Second, using network tool, the BsM is compared in terms of relations between buyers and sellers. Bipartite and projected networks are built. Different graphs are drawn in order to represent the market and the interactions between the different types of nodes. We analyse in a bipartite approach, the set of trust links between people as a social network. We compare both submarkets in terms of relations between buyers and sellers. Finally, under a dynamic framework, we look at the day and the season effect on the ratio. A linear regression, a GLM model, is used to show that on the one hand trust ratio affects repeated transactions, prices and quantities and on the other hand to determine wether this ratio is itself influenced by the day and the agents size.

> History matters. It matters not just because we can learn from the past, but because the present and the future are connected to the past by the continuity of a society's institutions. Today's and tomorrow's choices are shaped by the past. And the past can only be made intelligible as a story of institutional evolution
>
> North (1990)

Il est largement connu que l'organisation du marché joue sur l'allocation des ressources et sur les gains des échanges, et, avec les règles de formation des prix sur ces marchés, elle peut avoir un impact non négligeable sur l'efficacité du marché (Gode & Sunder (1997)). Ces deux points expliquent l'attention portée sur les comparaisons de l'architecture des marchés. Une littérature importante examine et analyse la différence entre deux structures : le marché des enchères et le marché de gré à gré.

Même si l'article pionnier de Bulow & Klemperer (1994) prouvait la prédominance du marché des enchères sur le marché négocié, à ce jour, il n'y a pas un consensus concernant la supériorité d'un marché sur un autre. L'idée de comparer le marché des enchères au marché de gré à gré a capté l'attention de Grossman & Stiglitz (1976). Par le biais d'un système de prix qui transmet l'information des individus informés aux individus en situation d'asymétrie d'information, Grossman & Stiglitz (1976) ont montré qu'il n'y a pas sûrement d'efficacité sur le marché décentralisé. Ils étaient convaincus qu'aucune réponse ne pourrait être fournie concernant la supériorité d'un mécanisme sur l'autre. Mais nous avons toujours pensé que la plupart des marchés, très souvent les centralisés, étaient les plus efficaces. En effet, la littérature qui dominait toutes les années 80 et 90 a accepté l'idée suivante qui était largement remportée surtout par Milgrom (1986) : le marché des enchères, assurant une même information parfaite à tout les individus, est considéré comme le plus efficient. En outre, l'information sur le marché affecte le comportement des agents : sur le marché de gré à gré, ils sont à la recherche de signaux crédibles (des signaux de qualité, et prix), contrairement au marché des enchères où l'information est connue (centralisée).

Plusieurs articles tendent à montrer que les deux structures centralisés et décentralisés, n'ont pas les mêmes résultats en termes d'efficience. Kirman, Moulet & Schulz (2008) concluaient que les profits sur les marchés décentralisés sont plus importantes que les profits des marchés centralisés, alors que Bulow & Klemperer (1996) et Milgrom (2004) ont montré que les enchères sont plus efficientes et prédominent le gré à gré. L'analyse de Bulow & Klemperer (1996) s'inscrivait dans la logique de Milgrom (1986). Ils ont montré que les enchères sont préférables quand les signaux des enchérisseurs sont indépendants. Alors que Mansur & White (2007) s'appuyaient sur l'idée qu'une structure organisée d'un marché améliore l'efficacité globale du marché. Leur objectif était de montrer comment les outcomes varient en passant d'un système bilatéral à un système d'enchères. De plus, l'étude empirique de Bajari, McMillan & Tadelis (2009) sur les contracts attribués dans le secteur privé de constructions de la Californie du nord, a montré que quand les projets sont complexes, les enchères ne fonctionnent pas parfaitement et le système de gré à gré est le plus efficient. Leur travail s'inscrivait dans la lignée des travaux de Goldberg (1977) et Manelli & Vincent (1995) qui suggéraient que les négociations pourraient être meilleurs que les enchères.

Somme toute, *"cette littérature identifie trois déterminants principaux du choix entre enchère et négociation : l'intensité concurrentielle sur le marché d'une part, le niveau d'expertise de l'acheteur dans l'organisation de la procédure d'attribution et la conduite des projets d'autre part, et, enfin, la complexité du projet, c'est-à-dire la difficulté à le contractualiser"* (Chong, Staropoli & Yvrande-Billon (2013)).

Notre but est de faire part de ce débat portant sur la supériorité d'un mécanisme de vente sur l'autre. Notre explication repose sur une notion différente de celle d'une littérature déjà existante qui se concentrait sur les institutions dans le but d'expliquer l'efficacité des marchés [9]. Cette littérature est une tentative d'explication de cette différence se basant sur les institutions et sur les règles du marché. Certes, les résultats du marchés peuvent être influencés non seulement par les institutions mais aussi par la structure du réseau social, et donc par les interactions des agents. En situation de risque, d'asymétrie d'information et d'absence de signaux de qualité, nos résultats tendent à prouver que les enchères ne sont pas l'unique solution (Maskin & Riley (1985)) et que le marché bilatéral pourrait être considéré comme un moyen pour diminuer ce risque en s'appuyant sur les liens interindividuels.

Depuis la fin des années 90, une littérature s'est développée en économie et a utilisé l'outil d'analyse des réseaux sociaux pour expliquer certains phénomènes économiques. Plusieurs économistes se sont basés par la suite sur les connexions et les interactions entre les agents pour expliquer des phénomènes que l'économie du classique n'arrivait pas à expliquer. De nos jours, les réseaux sociaux sur internet tel le réseau Facebook, twitter, Linkedin ont pris beaucoup de succès. Ce domaine n'est plus une nouveauté pour les économistes et les chercheurs. Nous parlons de réseaux de famille, amis, collègues, diplomates ainsi que des réseaux intellectuels (Lermercier (2005)). Les réseaux prennent différentes formes, néanmoins Barabasi & Bonabeau (2003) les ont décrits en tant qu'une structure formée par des joueurs attachés l'un à l'autre. Ainsi, Newman (2003) a mentionné que le type de réseau le plus simple est celui constitué de "sommets" qui sont liés par des "arrêts". Les réseaux sociaux, ensemble d'individus liés par des interactions sociales, ont attiré l'attention de plusieurs chercheurs puisqu'ils "s'infiltrent dans notre vie économique et sociale" (Jackson (2008)). Ils jouent un rôle important dans la transmission de l'information entre les individus (par exemple recherche d'emploi [10] et biens et services).

9. Pendant longtemps, et à partir de 1967, Grossman & Stiglitz (1976) montrent les marchés ont besoin de "parfaites" institutions qui créeront un système de prix permettant aux agents non informés d'acquérir l'information.

10. Trente à soixante pour cent de l'emploi sont à travers des liens sociaux (Bewley (1995))

Quoique les réseaux ont surgi au cours de ces dernières décennies, une large littérature sur les réseaux s'est développée et plein d'études théoriques et empiriques ont tracé leur importance : des études sur les réseaux téléphoniques (Onnela, Saramaki, Hyvonen, Szabo, Lazer, Kasbi, Kertesz & Barabasi (2007)), sur l'influence de la route aérienne sur la concurrence (Hendricks, Piccione & Tan (1995)) et sur l'impact des réseaux sur le bien et l'intérêt public (Bramoullè & Kranton (2007)). Les connexions personnelles et les contacts sociaux jouent un rôle important dans la diffusion de l'information (Bala & Goyal (1998)), dans les crimes et le travail (Calvo-Armengol, Verdier & Zenou (2007) et Rees & Shultz (1970)), dans le marché des co-auteur (der Leij & Goyal (2011)), dans la recherche d'un travail (Calvo-Armengol (2004)), dans le tabagisme et l'obésité (Christakis & Fowler (2007) et Christakis & Fowler (2008)). Par exemple Myers & Shultz (1951) ont montré que 62 % des travailleurs dans le domaine des textiles ont trouvé le premier emploi à travers les relations personnelles, 23% à travers les candidatures spontanées et seulement 15% à travers les agences et les annonces.

Cela fait plus de 40 années que la science considère les réseaux complexes comme des réseaux complètement aléatoires où la majorité des noeuds sont caractérisés par un même nombre de liens (même degré). Les caractéristiques des noeuds et la nature du lien n'étaient donc pas prises en compte (Barabasi & Bonabeau (2003)). Or, les réseaux ne sont pas identiques, certains sont caractérisés par des liens aléatoires alors que d'autres non. Les économistes utilisent la distribution des degrés des noeuds, la densité, l'assortativité et la transitivité pour analyser ces réseaux. La création des réseaux et leur influence sur les comportements des individus devraient donc être notées. L'idée de liens endogènes a été introduite tout au long de ces années, ainsi que l'idée la création des liens (Dutta & Mutuswami (1997) et Jackson & Wolinsky (1996)), de la stabilité des réseaux (Dutta & Jackson (2000) et Bala (2000)), de la dynamique et de l'évolution des réseaux (Kirman (1997), Goyal & Vega-Redondo (2000) et Jackson & Watts (2002)). Par contre, Barabasi & Bonabeau (2003) n'ont payé aucune attention au lien individuel et à la nature des noeuds dans un réseau complexe, contrairement à der Leij & Goyal (2011) qui ont étudié l'importance d'un lien faible par rapport lien fort dans un réseau.

De même, Montgomery (1991) a étudié l'intensité d'un lien dans le réseau. Son travail s'inscrit dans la logique de Granovetter (1973) dans la mesure où ces deux auteurs ont prouvé que les liens faibles sont plus important sur le marché de travail. Bien des années plus tard, Hansen (1999) a révélé l'importance du lien fort dans la transmission de la connaissance. Ainsi Kranton & Minehart (2001) dans leur article publié dans The American Economic Review, ont montré le poids des relations sociales dans la réalisation des échanges sur un marché intégré, et l'intérêt de la formation des liens au niveau individuel et même au niveau global. Plus récemment, des études faites par Galeotti & Goyal (2010) ont mis en valeur l'importance de constituer des liens avec un petit groupe d'individu possédant l'information. Ils ont présenté alors deux choix : le choix d'investir dans la formation de lien ou d'investir dans l'acquisition de l'information. Ils ont montré alors l'importance du coût de la formation de lien dans la construction du réseau. Par ailleurs, der Leij & Goyal (2011) ont distingué les liens forts des liens faibles et ont étudié l'influence de leur force sur la formation d'autres liens dans un réseau. Ils se sont basés sur l'étude faite par Granovetter (1973). Ce dernier a énoncé la théorie de «the strength of a weak ties» et a expliqué que « les individus avec qui on est faiblement lié, ont plus de chances d'évoluer dans des cercles différents, et ont donc accès à des informations différentes de celle que l'on reçoit». Suite à son enquête faite sur 300 cadres, Granovetter a conclut ce qui suit : « ce ne sont pas leurs amis ou leurs proches qui leur ont été le plus utiles pour les aider à trouver une situation, c'est au contraire les relations faibles- relations de connaissances- qu'ont beaucoup plus d'importance». Il a défini l'intensité du lien en tant que : *«Most intuitive notions of the strength of an interpersonal tie should be satisfied by the following definition : the strength of a tie is a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding) and the reciprocal services which characterise the tie».*

Un lien est tout ce qui rend possible ou tout ce qui ajoute une valeur à un échange bilatéral. Nous tenons à démontrer que ces liens, lien de confiance et lien personnel, réduisent l'asymétrie d'information. Dans quelle mesure ces liens facilitent-ils la coopération et les transactions, l'investissement et l'échange ? Ces liens créent un environnement économique qui rend plus faciles les échanges entre les offreurs et les demandeurs qui en bénéficient. Kranton & Minehart (2001) ont construit leur modèle sur l'hypothèse qu'un lien préalable est indispensable à tout échange. Les conséquences sur les prix sont intuitives mais ne vont pas toutes dans le même sens. Dans un travail plus empirique, der Leij & Goyal (2011) ont distingué deux formes de liens. Les liens faibles (lien indirect) et les liens forts (lien direct). Ils se sont demandés alors comment dans un réseau social il est possible de classer les liens entre ces deux catégories. Comment mesurer la force du lien ? Lequel a plus d'importance dans la diffusion de l'information dans le réseau ?

Cette thèse vient en continuité d'une littérature existante sur les liens entre marchés et réseaux qui montre comment les liens sociaux peuvent constituer une source d'information d'une part et d'autre part comment ils contribuent à créer de l'asymétrie d'information dans un environnement hétérogène. Notre thèse devra donc se poser la question des incitations à construire des liens ainsi que de leur efficacité et des conséquences en termes de prix entre deux structures de marché. L'objectif est d'étudier les comportements des agents sur un marché, un marché particulier de Boulogne-sur-Mer, marqué par la coexistence de deux systèmes de vente auxquels les acheteurs peuvent y accéder selon leur gré. Il s'agit d'analyser plus particulièrement le choix que chaque agent fait entre deux structures : le marché des enchères, un marché où l'information centralisée est commune à tous les agents et où à la fois les prix et la qualité sont affichés, et le marché de gré à gré, un marché où l'information est décentralisée et où le problème de l'évaluation de la qualité se pose. Les prix sur ce marché ne sont pas affichés même si la relation entre prix et qualité est connue ; nous faisons face donc aux marchés de biens complexes. L'information n'étant pas la même, nous s'appuyions sur l'idée que les agents se basent sur les relations interpersonnelles de confiance.

La possibilité d'ajouter la confiance permet de mieux expliquer les institutions économiques et le développement des formes institutionnelles (Berg, Dickhaut & Mccabe (1995)). En ce qui concerne la confiance, les économistes considèrent son importance dans les échanges. Mais sa definition et sa mesure restent ambiguë.

Initié par l'étude empirique de Rosenberg (1956), la confiance a occupé une place importante et croissante en économie. A ce jour là, la confiance reste une question sans réponse. Sa mesure et sa définition comme déjà mentionnée, constituent un problème majeur et qui persiste dans toute analyse. Même si plusieurs étaient intéressées par la confiance, nous avons toujours pas adopté une définition unique (Kramer (1999), Fulmer & Gelfand (2012)).

La confiance a fait l'objet d'intérêt de plusieurs chercheurs : des sociologues (Sztompka (1999)), des philosophes (Seligman (1998)), des psychologues (Yamagishi (2001)), des politologues et des économistes (Putnam (1993)). Les sociologues ont défini la confiance en se basant sur les expériences passées, les psychologues et les philosophes ont relié la confiance à l'amitié et à l'amour alors que les économistes l'ont expliqué par le fait d'être incité à des transactions futures et aux risques (Blau (1964)).
Cette confiance affecte de façon importante la croissance économique. Après Putnam (1993), des études ont été faites sur le rôle du capital social sur la croissances économique. Zak & Knack (2001) et Dincer & Uslaner (2007) ont montré une relation positive entre la croissance et la confiance en se basant sur une base de donnée américaine. Néanmoins, Helliwell (1996) a trouvé une relation négative sur son étude sur les pays de l'OCDE. Alors que Beugelsdijk & van Schaik (2005) en faisant une étude régionale, n'ont signalé aucune relation.

En plus, les marchés financiers ont adopté cette notion. Alan Greenspan dans la conférence des marchés financiers de la Banque Fédérale en Georgia en 2004 a mis en évidence l'importance de la confiance. Cette dernière étant fondamentale entre les participants pour le fonctionnement du marché, néanmoins les règles et les loi du marché [11] *"Recent transgressions in financial markets have underscored the fact that one can hardly overstate the importance of reputation in a market economy. To be sure, a market economy requires a structure of formal rules–for example, a law of contracts, bankruptcy statutes, a code of shareholder rights. But rules cannot substitute for character. In virtually all transactions, whether with customers or with colleagues, we rely on the word of those with whom we do business. If we could not do so, goods and services could not be exchanged efficiently. The trillions of dollars of assets that are priced and traded daily in our financial markets before legal confirmation illustrate the critical role of trust. Even when followed to the letter, rules guide only a few of the day-to-day decisions required of business and financial managers. The rest are governed by whatever personal code of values that managers bring to the table."*

De même Abolafia (1997) a signalé que les marchés apparaissent essentiellement comme des institutions sociales, dans lequel le comportement des individus est lié aux coutumes, normes (...) *"markets appear here as socially constructed institutions in which the behavior of traders is suspended in a web of customs, norms, and structures of control [...] traders [...] negotiate the perpetual tension between short-term self-interest and long-term self-restraint that marks their respective communities-and how the temptation toward excess spurs market activity"* . En outre, Kuhn (2005) va plus loin et soutient l'idée que les relations individuelles et la confiance sont fondamentales et nécessaires pour le fonctionnement du marché.

Des études empiriques et théoriques ont montré que la confiance réduit l'incertitude, le risque et les coûts. L'émergence de la confiance conduit à la dispersion des prix (Kirman & Vriend (2001)). Ainsi Vignes & Etienne (2008) ont prouvé que dans certaines situations

11. http ://www.federalreserve.gov/boardDocs/Speeches/2004/20040416/default.htm : last visit 15 February 2016

des relations stables entre vendeurs et acheteurs (loyales) peuvent entraîner des prix plus élevés. Kirman et al. (2008) ont démontré que le processus de marchandage est lié au type et à l'emplacement du business. La confiance et le marchandage procurent aux consommateurs des prix meilleurs que le prix moyen. Ce résultat était en contradiction avec celui de Weisbuch, Kirman & Herreiner (2000), ou la confiance a conduit à une hausse des prix (une explication de cette difference entre ces deux résultats peut être lié à la qualité du produit).

Meidinger, Robin & Ruffieux (1999) ont conclu que les individus font confiance quand ils sont conscient que cette confiance va produire un profit maximal. *" En particulier, dans des situations où la confiance peut être utilisée pour obtenir un gain mutuel, le résultats expérimentaux montrent non seulement que certains individus sont disposés à faire confiance mais également que d'autres sont incitées à la réciprocité en présence de manifestations de confiance"* . Leur méthode expérimentale a permis d'identifier et de mesurer la confiance entre les agents. Le résultat du jeu de l'investissement a été que 84% de l'échantillon font confiance.

Guiso, Sapienza & Zingales (2009) ont étudié la confiance bilatérale entre les pays européens. La confiance n'est pas liée aux caractéristiques du pays mais plutôt aux aspects culturels comme la religion, l'histoire, les conflits, la langue, et les différences génétiques et somatiques. Cette idée n'était pas supportée par Alesina & Ferrara (2002). Ces derniers ont démontré que la croyance religieuse et les origines éthiques n'ont pas d'influence significative sur la confiance alors que la race apparaît comme un déterminant principal. Et donc, la confiance est corrélée à la communauté (hétérogène ou non) où les individus vivent (discrimination entre les minorités, femmes et noirs) et ses caractéristiques (revenue, éducation). Uslaner & Brown (2005) se basant sur une base de donnée des Etats-Unis, ont révélé que la confiance diffère entre le pays et les Etats (Holm & Danielson (2005) different résultats de confiance entre Suède et Tanzania).

Plan de la thèse

Ce projet continue donc à réfléchir sur l'influence des différentes formes de liens couplés avec des graphes de topologies différentes. Son objectif principal consiste à étudier l'influence de la structure du marché sur la construction des liens sociaux (liens de confiance). La thèse aura deux dimensions : une première dimension qui portera sur des questionnements sur l'influence des différents liens sur un réseau, la question de définition d'un type de lien de confiance et les problèmes dans sa mesure, et une deuxième dimension qui consistera à tester ces liens interindividuels. Là, il ne s'agira plus de collaborations mais d'échanges entre individus de types différents (vendeurs et acheteurs). Ces résultats permettront de voir en quoi les relations interpersonnelles affectent les prix et dans quelle mesure elles sont influencées par la structure d'un marché. On exploitera pour cela des bases de données fournies par le ministère de l'agriculture sur des marchés au poisson du nord de la France : le marché de Boulogne-sur-Mer. Avec deux structures différentes (processus d'enchères et échanges négociés), ce marché fournira un riche terrain d'investigation pour mieux comprendre l'influence des liens sociaux et leur robustesse à travers des formes d'échanges très différentes. Les données fournies sont détaillées et permettent de suivre les individus à travers leurs transactions quotidiennes.

En plus d'un aperçu de littérature détaillé, la thèse comporte trois chapitres correspondant chacun à une étude distincte qui abordent le fonctionnement de ce marché par des approches complémentaires où également une introduction de ce marché très particulier est faite.

Chapitre 1 : Quantifying the differences between the auction and the negotiated market : the role of the structure of interactions

Au début des années 80 et 90, il était généralement accepté parmi les économistes, que le marché avec une structure centralisée, comme le marché aux enchères, est plus efficace qu'un système décentralisé (le marché de gré à gré). Cela est expliqué par le fait que sur le marché des enchères tous les acteurs disposent de la même information, alors que sur le marché négocié, l'information détenue n'est pas la même. Même si de nombreux travaux comparent ces deux structures, nous ne pouvons toujours pas conclure une prédominance d'un système sur l'autre. Mais depuis quelques années, une attention particulière sur la structure des interactions a capté l'attention de plusieurs économistes (**?**, Gallegati, Giulioni, Kirman & Palestrini (2011*b*), and Bottazzi et al. (2005)) dans le but de pouvoir mieux expliquer ces différentes structures.

Le marché de Boulogne-sur-Mer, le marché le plus important en France en termes de quantité, constitue un terrain intéressant nous permettant de comprendre et de résoudre ce problème. Ce vieux marché, qui avait fonctionné d'une manière décentralisée pour longtemps, a été mené suite aux réglementations de l'UE à adopter une structure centralisée. Cependant, ce nouveau mode de fonctionnement n'a pas convaincu les acteurs économiques et finalement en Avril 2006, le marché de Boulogne-sur-Mer était caractérisé par la coexistence de deux formes de marché : les enchères et le gré à gré.
Une base de données détaillée concernant les transactions quotidiennes est disponible par AgriMer France. Cette base permet une comparaison de ces deux sous-marchés dans des conditions économiques, saisonnières et climatiques similaires.

Ce papier s'intéresse sur la structure des interactions sociales crées entre les acteurs des deux sous-marchés (acheteurs et vendeurs). Ces interactions peuvent être décrites par le biais d'un réseau complexe où seulement les noeuds de deux différents types peuvent être connectés. Les liens de ce réseau sont les interactions faites entre ces noeuds représentant les acheteurs et les vendeurs. Le réseau ainsi obtenu est bipartite. Ce dernier, pondéré par les interactions entre les agents sur toute la période est étudié.

Nous résolvons ce problème en appliquant les outils et les concepts utilisés pour analyser les systèmes mutualistes écologiques (Burgos et al. (2009)). Ces systèmes sont caractérisés par les interactions entre des acteurs différents, comme dans le réseau des plantes et des pollinisateurs. Cette méthodologie nous permettra de voir si les deux mécanismes de vente du marché de Boulogne-sur-Mer sont similaires. Nos premiers résultats montrent que les structures des interactions sociales sont assez différentes. Pour cela, on définit un indice de «fidélité» entre les différents couples formés. La distribution de probabilité de cet indice de fidélité ressemble à une "power low" sur le marché négocié alors qu'elle montre une diminution plus nette sur les enchères. Cela met le point sur une fidélité plus importante sur le marché négocié et sur un seuil de fidélité sur les enchères.

Chapitre 2 : How long does it take a buyer to find his match ? Trust in duration model

La deuxième originalité de cette thèse est d'étudier en se basant sur le modèle de survie, la création de la confiance. Etant donné que la définition de la confiance, l'identification de ces déterminants et sa mesure restent toujours un problème, une étude originale de cette confiance est fournie dans cet article. Cette étude est faite du côté des acheteurs. Arrivant sur le marché de Boulogne-sur-Mer, l'acheteur a le choix entre deux structures : les enchères et le gré à gré. Un arbitrage prend lieu donc entre un marché où l'information est centralisée, et un marché en situation d'asymétrie d'information. L'acheteur décidant de négocier, se trouve alors dans une situation d'asymétrie et par la suite dans un état de recherche. Sur ce marché de gré à gré, l'acheteur fait face à plusieurs vendeurs avec qui, il négocie et échange. Deux situations sont notées : (1) il peut rester dans cet état de recherche, rencontrer plusieurs vendeurs et donc avoir plusieurs connexions (degré élevé) ou (2) il peut passer de l'état de recherche au cercle de la confiance et donc par la suite restreindre ses connexions à ses vendeurs préférés. On peut voir une diminution de son degré au cours du temps.

Se basant sur ce degré comme indice de transition d'un état à l'autre, le modèle de survie est testé. Ce papier consiste donc à différencier entre les différents acheteurs en considérant les variables suivantes : quantité, espèce, nombre de présence et le nombre de connexions (degré). Par la suite, deux approches non-paramétriques et paramétriques sont utilisées pour montrer comment des structures différentes de marché peuvent jouer différemment sur la confiance et sur la durée de transition entre la recherche et le cercle de confiance.

Pour les trois différentes catégories des acheteurs : (1) les acheteurs qui préfèrent les enchères, (2) les acheteurs qui préfèrent le négocié et (3) les acheteurs qui sont indifférents entre les deux structures, on trace la fonction de survie pour voir si le comportement des acheteurs selon leurs catégories est différent entre les deux structures. Les résultats obtenus liés à la taille des acheteurs semblent intéressants. Les acheteurs de toutes tailles indifférents entre les deux structures sont plus atteints par la confiance sur le marché négocié que sur le marché des enchères. Les acheteurs les plus grands, préférant les enchères, ont zéro confiance, alors que ceux préférant le négocié, acheteurs de petites tailles, choisissent ce marché tout en se basant sur la confiance.

Chapitre 3 : To trust or to bid : an empirical analysis of social relationships on a fish market

Le dernier article regroupe les trois grands axes de la thèse : structure du marché, influence de la confiance et réseaux.

Une analyse de l'influence de la confiance sur le fonctionnement d'un marché aux poissons, où les agents peuvent choisir entre enchérir ou l'échange grâce à des transactions bilatérales est tracée. Même s'il est connu que dans l'économie, la confiance joue un rôle important sur les transactions, sa définition et sa mesure, aussi loin que nous le savons, restent très difficile à atteindre.

A partir de l'analyse empirique du marché de poisson de Boulogne-sur-Mer, un marché où les agents ont le choix entre la vente aux enchères et les échanges bilatéraux, nous montrons comment la structure des réseaux sociaux est différente entre ces deux mécanismes de vente. Nous proposons par la suite une mesure de confiance, fondée sur la dynamique de rencontre entre les agents. L'idée est donc de fournir un indice de confiance. Cet indice sera utilisé sous deux dimensions : une première dimension économétrique afin de voir l'influence de cette confiance sur les prix et les quantités et une deuxième dimension d'analyse de réseau, qui consiste à tracer des réseaux bipartites et projetés.

Pour se faire, nous définissons le niveau de confiance entre deux personnes par le nombre de rencontres (nombre de jours où deux personnes échangent ensemble), par rapport au nombre de rencontre que ces mêmes personnes auraient fait au hasard. Plus ces deux personnes échangent ensemble, plus le niveau de confiance est important. Nous vous proposons cet indice original basé sur les rencontres répétées entre acheteurs et vendeurs. Cela nous permettra de faire la distinction entre les rencontres aléatoires et ceux provenant des relations de confiance.

Une fois cet indice est défini, nous comparons par la suite la construction d'un réseau de confiance tout en tenant compte de la structure du marché. Ensuite, un modèle de GLM à effet fixe, où les statistiques du réseau sont utilisées comme variables, montre comment la centralité peut influencer les prix des transactions. Cependant, deux autres estimations GLM s'intéressent sur l'effet de l'indice de confiance et du nombre de transactions faites sur les prix et les quantités.

Somme toute, cet article présente une étude empirique de la dimension sociale et des liens de confiance : leurs influences sur les outcomes des transactions. Finalement à l'aide des outils d'analyse des réseaux, l'importance de la structure du marché sur les réseaux sociaux est illustrée.

1 Related Literature

> History matters. It matters not just because we can learn from the past, but because the present and the future are connected to the past by the continuity of a society's institutions. Today's and tomorrow's choices are shaped by the past. And the past can only be made intelligible as a story of institutional evolution.
>
> North (1990)

Markets organisation has long inducted a rich set of questions to economics. Smith (1962) and Smith (1964) unveiled that the plan of actions employed to aggregate information and to determine prices can strongly affect market's efficiency. Hence, a new field of market designs has emerged in order to underline how rules and protocols can reveal information, boost market performance and determine efficient prices. But, few literature studied the influence of different market organisations on prices and quantities. The article of Roth (2002) pointed out the rules and the procedures of the market that help to reveal information, to boost the performance of the market and to discover efficient prices.

Furthermore, it is known that institutions set the rules of game in a society and the humanly devised constraints that shape human interactions. What institutions are and how they influence transactions and production costs is the key of North (1990) analysis. In his famous book, he showed that "the evolution of institutions that create an hospitable environment for cooperative solutions to complex exchange provides for economic growth". Hence, *correct* institutions are vital to create efficient market. As Stiglitz mentioned : "one of the recent revolution in economics is an understanding that markets do not automatically work well, design matters". The market architecture and price formation played an important role in market efficiency (see Sapio et al. (2011)). Gode & Sunder (1997) defined allocative efficiency as the ratio of actual gain over potential gain from trade. To be efficient, markets need good institutions in order to realise a price system that helps uniformed agent to acquire information (Grossman & Stiglitz (1976)). Some articles tended to prove that centralised and bilateral markets, the two different market designs, do not have similar effect and their results are not the same. For example, Kirman et al. (2008) showed that profits on decentralised markets are higher than centralised one, unlike Bulow & Klemperer (1996) and Milgrom (2004) who proved that centralised market are more efficient and predominate the decentralised one. Hence, large literature focused on institutions to explain efficiency in markets.

Moreover, not many have tried to explain market efficiency by something more than institutions. Obviously, markets outcome can be impacted by the structure of social networks, by agents interactions. " Markets take on a different meaning. Markets allow us to access the vast amount of knowledge that are scattered amont the people in the world" (Hausmann & Hidalgo (2014))

For many years, social context was considered as second order in economic interactions. But since, "social economics" has emerged to become a primary driver of behaviours and outcomes (Jackson (2007)). Since the 90's, a new literature has been developed using social network to underline agents behaviours. Social networks were then defined as networks composed of individuals constituting the nodes, which are linked by social interactions. The influence of social interactions on the functioning of markets was studied. Social settings have been necessary to sociologists and have been largely explained by Granovetter (1985). Granovetter (1973) explored the intensity of social ties in network. He introduced the idea of an intense link between two people : "Most intuitive notions of the strength of an interpersonal tie should be satisfied by the following definition : the strength of a tie is a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding) and the reciprocal services which characterise the tie".

Is trust a primitive in economic models of behaviour ? The possibility to add trust as part of a rational choice paradigm explains in a better way economic institutions and it must be taken into account when explaining the development of institutional forms (Berg et al. (1995)).

Economists have long considered trust important in transactions. However its finding and measurement are still very ambiguous. Do *correct* institutions generate trust ? Or does trust fortify institutions ? In this thesis, social networks concept is used to understand market structure and to compare their efficiency ; trust between agents will be notably used to define interactions on a particular fish market. Our goal is to study agent behaviour on two different structures. Behind the questions previously asked on the influence of social links on the market outcome, it is indeed the question of markets organisation and their efficiency that has to be raised. Two different structures are explored : a market where information is common to all and where prices and quality are displayed, and a market where prices and quality are not displayed. In the event where quality and prices are not displayed, agents search for information. A reason to compare the market functioning using social interactions via trust.

The idea of **comparing** centralised and decentralised markets in terms of efficiency, emerged with the pioneer article of Grossman & Stiglitz (1976). By implementing a price system that efficiently convey information from informed to uninformed individuals, they assured that decentralised markets are not the most efficient [1]. Moreover, they were convin-

1. In financial decentralised markets, arbitrage process showed that information is not complete

ced that no answer can be given whether centralised information market designs are more efficient than decentralised markets [2]. The idea that centralised market, also known as auction market, is more efficient than the decentralised market has been proved by Milgrom (1986) in the 20th century. In addition, information availability in centralised and decentralised markets can influence agents behaviours. Unlike the auction market where information is already known (centralised), agents will look for credible signals in an imperfect market (the negotiated market) to obtain better prices and lower costs. Another comparison of these two mechanisms was made by Blouin (2003). A centralised market is a market occupied by a large number of agents who have simultaneous access to some trading opportunities, so that a single price prevails. He described decentralised trade as an operation in which agents are randomly paired, a pair of one buyer and one seller. Buyer and seller bargain over price at which transition occurred. Thus exchange takes place if agreement is settled ; otherwise pair is broken and agents look for new partners. He mentioned that in the centralised market, trade operations have no frictions (as transactions costs), unlike in the decentralised market which is occupied by a large number of agents and marked by the cost of delay considered as its friction.

Many economists have built models that compared decentralised equilibria to equilibria of models with centralised trade. The analysis of Bulow & Klemperer (1996) was in line with Milgrom (1986) ; they showed that auction is always preferable when the signals of bidders are independent. Moreno & Wooders (2004) implied that if the company's board expect at least one extra serious bidder to appear in an auction, then it should generally not negotiate and should directly begin an auction [3]. The work of Blouin (2003) came as a contrast to models on centralised trade with adverse selection. He showed that if trade is decentralised, then all units of good are traded, and all agents have positive ex-ante

2. it depends on the cost of operating a centralised information mechanism.

3. Supposing that, bidders have no bargaining power in a negotiation and sellers negotiate optimally making credible commitments (that is not the case in real life) Moreno & Wooders (2004) concluded that their basic result does not overstate the efficacy of auction relative to negotiated

expected payoffs. Mansur & White (2007) said that an organised market design improve overall market efficiency. They showed interest in the competitive electricity markets. In their article, they stated how outcomes change from a bilateral system of trade to an auction one and how in this competitive market, markets organisation affects performance, efficiency, and prices. They proved that "adopting a well-chosen market design wield improve market efficiency in areas where decentralised, bilateral practices prevail". Kirman & Moulet (2008) compared descending auction and negotiation. They showed by the use of computer simulations that negotiation allow to "poor" buyers to buy even if auction are more interesting when it comes to buyers who have a higher reservation price. Moreover, Chong et al. (2014) provided an empirical analysis by examining the entire set of public procurement work contracts in the construction sector. They found "regularities regarding the choice of awarding procedures by public buyers" (see also Chong et al. (2013)). In another empirical analysis by Bajari et al. (2009) on a private sector building contracts awarded in Northern California, they demonstrated that when projects are complex, auctions perform poorly and negotiated system trades are more efficient. This is in line with the study of Goldberg (1977) and Manelli & Vincent (1995) who proved that negotiations patterns may be better than auctions. *To sum up the propositions derived from the literature, the trade-off between auction and negotiation in public procurement is assumed to depend on (1) the level of complexity of the project to be procured, (2) the potential for competition, (3) the pre-existence of relational contracts between buyers and sellers, and (4) the competencies of buyers regarding the organisation of competitive tendering* (Chong et al. (2014)).

Our goal is to be part of this debate by providing an explanation to this trade-off between the two mechanisms. Which way is more profitable to exchange goods, centralised or bilateral market ?

What are the differences between these two mechanisms ?
A centralised market is a market where price and quality are displayed, unlike the decen-

tralised one that is marked by uncertainty. The amount of information differ among both submarkets. General equilibrium model were the center of interest until the seventeenth, when a new literature has expended on the bases of the Lemons Model of Akerlof (1970). The question of quality assessment and the problem of information and its influence on agents choice has occupied many attention and was treated in the beginning of the 1970. Thus the importance of quality and information on decentralised market were then introduced. Many economist were interested in the amount of information on market and how it influences transactions. A pioneer article for Akerlof (1970), introduced a whole new idea in the 70's with his research model on used cars (Lemons). His model considered adverse selection because quality (good or bad quality) is better seen by sellers than buyers. Therefore, the idea of a complex good emerged. Unlike an homogeneous good, it is hard for buyer to identify quality of complex good and to differentiate between them. Different qualities exist and a degree of information's asymmetry is present between the buyers (who are unable to differentiate between the goods quality) and the sellers (who are aware of what they produce). This market is known as a decentralised market in terms of information as agents are not fully informed about the market situation. "The existence of goods of many grades poses interesting and important problems for the theory of the markets". Akerlof (1970) questioned inherent characteristics of agents and heterogeneity in good quality. "The difficulty of distinguishing good quality from bad is inherent in the business world", the price represents therefore an aspect for good quality. Agents looking for product do not possess *ex-ante* a perfect information about the quality of goods. The perceived quality in previous periods can be used as a signal for quality in future periods. After Akerlof, quality also emerges with Karpik (1989). Recent studies showed that the quality depends "more on a social organisation". Karpik (1989) introduced the idea of economics of quality where "the judgment is in fact a particular form of organisation of economic life ".

A strand of literature has looked on centralised and decentralised markets when information is perfect. On centralised market where information is perfect, emerges the Walra-

sian equilibrium. In a pioneer article, Rubinstein & Wolinsky (1985) built a steady-state model on decentralised market where agents possess perfect information and came by the followings results : "all agents receive positive payoffs, even when the Walrasian model predicts otherwise". As for Gale (1987), he worked on the steady and non-steady-state and came up with the conclusion that both models yield to Walrasian outcomes.
Another strand of literature was interested in imperfect information. Wolinsky (1990) proved that even if uninformed agents stayed longer on market in order to get more information, they cannot guarantee positive payoffs. As for Moreno & Wooders (2004), not all agents trade and high quality sellers receive zero payoffs ; total gains from decentralised trade are always higher than under centralised one.

How can we describe the centralised and the decentralised markets ?
Centralised auction market : Auction origin from Latin, means "I increase". Largely known, it was an unusual selling procedure and a method to exchange goods. Nonetheless, auction has a long history that has began with the marriage market of Babylon 500 B.C. where women for marriage were sold each year. According to Herodotus, beautiful women were trade in the first place at a high price. After that, and for many years, not only women for marriage were bought, but romans soldiers, slaves, empires, houses, household furnitures as well as art works were auctioned. Auction market was extended all over the world and was developed at a fast way two decades ago.

Several auction forms exist and differ over countries and over the type of goods. The auction mechanisms determine who will get the good in question and at what price. Three auctions are well known : buyers or demand auction (one seller vs many buyers), sellers or supply auction (one buyer vs many sellers) and double auction (many buyers and sellers). As for the types of auctions, four types of the most frequently mentioned bid are classified as follow : English auction, Dutch auction, Vickrey auction and Sealed first price auction. Those auctions are classified as primary auctions. Not to mention that secondary auctions are also used including all-pay, auction by candle, bidding fee, buyout, combinatorial, Japanese, mystery, senior, silent, Walrasian, no reserve and reserve auctions. So why auction structure ? As information is common to all agents, auction is a way out from risk. Maskin & Riley (1985) worked on auction markets. In auction theory, the concept of revenue equivalence is one of the main findings. The answer of Maskin & Riley (1985) is the revenu equivalence theorem. They pretended that with auction, even if agents are neutral or risk averse, it will not affect the exchanging process. Maskin & Riley (1985) claimed that : "the Revenue Equivalence Theorem asserts that when each bidder's reservation price for a unit of an indivisible good is an independent drawn from the same distribution, and bidders are risk neutral, the sealed-bid auction generates the same expected revenue as the open auction". An auction mechanism - where bidder with the highest valuation for good always wins and the one with the lowest valuation have a zero surplus, and where all bidders are risk neutral and drawn from a strictly increasing distribution - yields to the same expected revenue for sellers.

In this thesis we show that when problem of uncertainty, aversion and asymmetry of information emerge, agents have another alternative : negotiation.

Another alternative to procure goods and services is the negotiated market, **a decentralised bilateral system of trade**, where each transaction is negotiated independently between buyers and sellers. Buyers and sellers bargain over the prices (Kirman, Schulz, Hardle & Werwatz (2005) studied the influence of negotiation on price) and the quantity. No third person, as the auctioneer, leads the traffic. In this mechanism agents have to auto-organise. The information that buyers and sellers have is not same. Buyers and sellers can choose with whom to transact unlike the auction market where sellers are unable to make decision to whom to sell. The agents characteristics, the influence of their beliefs and the social interactions have important effect on buyer and seller behaviour on negotiated market. The efficiency of unstructured bilateral markets is determined by how buyers and sellers are matched (Mansur & White (2007)). It is difficult on these markets to observe and characterise participant's information.

Sellers are rational and want to extract the maximum surplus they can. They need to transmit and to report information of what they own to buyers. Hence, they can send signals to buyers in order to indicate the goods quality while buyers try to distinguish between a credible and non credible signals.

Buyers are aware of this situation, imperfect or asymmetric information related to goods quality and characteristics. As buyers are rational, they are searching for better prices (the lowest one they can find) taking into account the searching cost they are willing to pay. As for Wiggins & Lane (1983), in view of their budget constraint, buyers will stop searching when their utility for searching for a new seller is lower than not searching. They will consider searching costs and then fix the number of sellers they can visit. Buyers decide about a reservation price in a negotiation game that is equal to the maximum price they are willing to pay. We can refer to the reservation price as the walk away point in a negotiated agreement.

As it was previously mentioned, our aim is to contribute to this debate by providing an explanation to this trade-off between the two mechanisms. Our explanation depends on a bigger matter. As Maskin & Riley (1985) claimed that auction is a way to reduce risk, we seek to prove that when problem of risk aversion arises, agents use another alternative to reduce uncertainty. Decentralised market are hence very important as the interactions between the agents and the agents behaviour influence this debate. Social network should have a part in our debate.

The market as a social network : Economic is primarily the study of market, limited to institutions in which persons interact through a process price formation. In the first half way of the century, institutional economics concentrated on the neoclassical theory of general competitive equilibrium in idealised competitive markets. However, incomplete market blocked economy from attaining the social optimum. In the seventeenth, this idea was ended and the following phase was launched : the concept of noncooperative and dynamic game theory. It enabled economists to analyse and study market structure. Game theory motivated economists to focus on interactions. As a consequence, economists studied phenomena as the evolution of social norms and borrowed from sociologists the social concept. Thus, many economists used connections and interactions among agents to explain some phenomena. Nowadays, social networking websites as Facebook, twitter, LinkedIn have highlighted social networks now more than ever. They recently gained an interesting popularity related to the number of users. Social networks are not a new matter to economists and to researchers. Networks include family, neighbours, friends, diplomatics, colleagues, religions and intellectual networks [Lermercier (2005)], and they came up with many shapes and forms. Nevertheless Barabasi & Bonabeau (2003) described it as a structure made up of players that are tied up together, *"The brain is a network of cells connected by axons, and cells themselves are networks of molecules connected by biochemical reactions"*. Newman (2003) mentioned that "a set of vertices joined by edges is only the simplest type of network". Social networks are a set of people joined by social interactions, they attracted considerable attention because they describe links as a relation between people. "Social networks permeate our social and economics lives" (Jackson (2008)), they are necessary in transmitting information between individuals (about job opportunities [4], services and goods).

Many economists have realised that social context is necessary to pilot behaviours and outcomes in many economic interactions. Their growing curiosity to social structure was at the same rate to behavioural economics. Social settings has been fundamental to

4. Thirty to sixty percent of all employment relations are estimated to be result of personal ties (Bewley (1995))

sociologists for some time and it was mostly ignored by economists until the last decade. The recent interest appeared in order to explain some observed economic phenomena when economic models could not. However, humans behaviours plays an important role when representing economic decisions makers. "The substantial body of work in sociology tells us (among other things) how and when networks matter, and helps us describe them from a variety of structural perspectives. The economic perspective brings decision making actors and takes incentives as a serious input, and with an eye to efficiency and welfare measures, can yield new insights regarding the formation of networks and the influence that networks have on behaviour" (Jackson (2007)). Economists lied on rational choices to study social context. As individual are rational, they will choose with whom they interact, maintain beneficial relations, or avoid and remove links that are not useful. Their choices depend on the cost and benefit of linking, so actors somehow weigh costs versus benefits. Other economists tended to explain why it is this way. Why analysing social networks ? First, analysing and modelling social interactions is supposed to be very helpful and second networks structure can control outcomes.

Despite that networks arisen in the last decade, there is a large literature on networks developed in the last years and lots of theoretical works showed the importance of network. We can find application on the mobile phone conversations network (Onnela et al. (2007)), the influence of the airline route design on competition (Hendricks et al. (1995)), the impact of networks in the public good games (Bramoullè & Kranton (2007)). Personal connections and social contacts can play an important role in the diffusion of information (Bala & Goyal (1998)), criminal and labour (Calvo-Armengol et al. (2007)), co-authorship (der Leij & Goyal (2011)), finding a job (Calvo-Armengol (2004)), smoking and obesity (Christakis & Fowler (2007) and Christakis & Fowler (2008)). Some economists were interested in studying its importance, for example, in order to get jobs as Myers & Shultz (1951) and Rees & Shultz (1970). Myers & Shultz (1951) showed that 62 percent of textile workers find their first job through social contact, 23 applied by direct application and only 15 percent through agency and ads. The link between social network and labor market continued. Labor markets are decentralised markets where information is transmitted via personal links, what shape wages, mobility, education and employment. Unemployed people increase information about jobs via their employed friends. The model of Calvo-Armengol (2004) and Calvo-Armengol & Jackson (2009) showed that increasing the number of worker friends increase the employment prospects the worker. Another example on the influence of social networks is about the criminal behaviour and how criminal activity grows with neighbours criminal activity (Glaeser, Sacerdote & Scheinkman (1996)).

For more than 40 years, science treated all complex network as being completely random where most of the nodes have more or less the same number of links. In Barabasi & Bonabeau (2003) researches, the characteristics of the nodes and the type of the links were not considered. But recently, endogenous link creation has been studied, how links are formed between agents (Dutta & Mutuswami (1997) and Jackson & Wolinsky (1996)), the stability of networks (Dutta & Jackson (2000) and Bala (2000)), the dynamics of network formation and the evolution (Goyal & Vega-Redondo (2000), Jackson & Watts (2002), Kirman (1997)). But Barabasi & Bonabeau (2003) payed no heed to the individual link and the nodes type in complex networks, unlike der Leij & Goyal (2011) who explored the hypothesis of the strength of a weak tie and studied if weak ties are more critical than strong ties in a network. Bernasconi & Galizzi (2010) referred to social network as "the complex systems of social relationships which occur within a group of individuals". Many article constitute a road between economist and sociologist literature. Granovetter (1973) and Montgomery (1991) also studied the length of ties in networks. Both of their works proved that weak ties in labor markets are more important. But after few years, Hansen (1999) revealed the importance of strong ties in transmitting knowledge. Other works tended to prove that the link between network structure and economic outcomes is throughout economic cooperative game theory. Therefore communicating and generally cooperating can lead to higher production (Myerson (1977)).
Jackson (2009) tried to determine if a person's decision is influenced by his or her friends

acquaintances. People connect with others who have same characteristics that some of them are hidden and cannot be observed by researchers. Endogeneity in network analysis is also studied. Do people adapt their behaviour to that of their friends ? People adjust their friendships and their behaviour based and in response to their friends behaviour (Kandel 1977). The individual behaviour is influenced and influences other individuals behaviour. The stronger influences are with people with whom we interact more often than the people who we see less or do not interact at all. Links as personal relationships play an important role in the dissemination of information which in turn guides the individual decisions. But the creation and maintaining of the link require time and resources. Reducing the cost of linking leads to decrease the personal acquisition of information and to increase the number of links in the network. Galeotti & Goyal (2010) showed that " The law of the few - the phenomenon where a large majority of individuals get most of the information needed for their decisions from a very small subset of the group - is a robust equilibrium phenomenon in such a model". A small subset of individuals collect the information while the remaining individuals in the network form links with this small group to access to the necessary information. Kranton & Minehart (2001) and Kranton & Minehart (2000) showed that linking is necessary for any transactions, as for Corominas-Bosch (2004) she highlighted how an agent in a network can power its economics activity.
In the Jackson & Wolinsky (1996) connections model, agents gain from having directed as indirected links. Comparing linking cost to marginal gain, a complete network or an empty one is created. There are many discussion regarding network formation ; as function in network, agents can pay each other and can bargain over the benefits of networks (Myerson (1977), Jackson & Wolinsky (1996)). Each link created has his own particularity. This particularity is the result of the diversity of links in a network. "'Because personal networks rarely operate as solidarities, people cannot count on all the members of their networks to provide help all the time"'(Plickert, Wellman & Côté (2007)).

Pushing a bit further, networks are not similar. Some of them are characterised by random link formation, some are not. Economists use clustering, density and distance to analysis networks. But they were also concerned in how networks are formed and how they influence behaviours. As externalities play an eminent role in networks setting, the link between networks formation and economic inside can be explained. Starting with Granovetter (1973) work that showed how informal connections and contacts are crucial in finding a job. He showed how a weak tie is more important than a strong one on the labor market. Bernasconi & Galizzi (2010) mentioned that the degree in networks gives an important information on the social interest, behaviour, decisions and outcomes of an individual. Hence Calvo-Armengol (2004) results are that even price and trades are affected by the connections in social networks.

Questions about how society's behaviours are influenced by networks structure and how the individual's position in a network affects its behaviour may be asked. Many economists tried to examine and to model how network structure shapes economic outcomes. On one hand, communication and learning are primary in transmitting information and behaviour in networks as word of mouth. On the other hand, its not about information's transmission and flow, but *in lieu* its about patterns interactions and externalities that affect choices. Karpik (1989) proved that "social relationships are the dominant practice" as 60% of individuals take the first contact with their lawyer as a result of personal and social relationships. Similarly, the reputation, merits and the name held important in the customer choice. He recalled the notion of "snowball" which emphasises the importance of time and slope, length and reputation in the choice. Hence, the final choice considered the required information exchanged between several people in a relation systems called trade-networks.

In this thesis we rely on the definition of Granovetter (1973) in order to define the intensity of a link. As nodes in a network are not linked in the same way, we consider the following definition :

> *"Most intuitive notions of the strength of an interpersonal tie should be satisfied by the following definition : the strength of a tie is a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding) and the reciprocal services which characterise the tie"*

It's easier to trust someone you know. (Goyal (2009))

During the last decade, a rush of empirical research on trust occurred. It has begin with Rosenberg (1956) with his survey on trust "generally speaking, do you believe that most people can be trusted or can't you be too careful in dealing with people ?". After Rosenberg (1956), scholars have focused on the role of trust, reputation and social norms. Nowadays, trust remains an unresolved concerns. It is not something easy to define and to measure. Even if many were interested in trust, there is no common definition (Kramer (1999), Fulmer & Gelfand (2012)).

Trust has been interpreted in many way and by many scholars (Abbas (2014)). Sociologists (Sztompka (1999)), philosophers (Seligman (1998)) , psychologist (Yamagishi (2001)), political scientists and economists (Putnam (1993), Gallegati et al. (2011*b*)). Sociologists defined trust using past experiences, psychologists and philosophers related it to friendship, to love and to trustworthiness, and economists explained it in order to look at the incentives of future exchanges and risk (See Blau (1964) who outlined that, exchanges developed at a slow rate ; starting with small transactions that demand little trust where agents witness to their trustworthiness, then expanding their relations through more important transactions). As for Cabral (2005), he defined it as follow : the willingness to get engaged in a collaborative relation without knowing how the others are going to behave. You anticipate cooperation and commit the trade without guaranteeing the other person's behaviour. Cooperation's in today's game is a signal of future cooperation. Cabral (2005) referred to trust by essentially two mechanisms : the repeated interaction and the Bayesian updating of beliefs [5]. Economists claimed that a link exists between cooperation and trust. Nahapiet & Ghoshal (1998) affirmed that "'trust lubricates cooperation, and cooperation itself breeds trust"'.

Trust is linked to many themes and majors. Related to individuals characteristic, it is considered as a way out of risk. It can also affect economics growth, bargaining games, reciprocity and behaviour.

Since Putnam (1993), many economists were interested in how social capital can affect growth in economics. Zak & Knack (2001) and Dincer & Uslaner (2007) for example showed a positive relationship between growth and trust using data from the US states. However, Helliwell (1996) found a negative relation on his study for high-income OECD countries. On the other hand, Beugelsdijk & van Schaik (2005) using regional data, didn't find any relationship. Algan & Cahuc (2010) focused on the inherited component of trust and studied how it influences economics growth. Agents can rely on trust when deciding about investing. So, "when people trust each other, transaction costs in economic activities are reduced, large organisations function better, governments are more efficient, financial development is faster : more trust may spur economic success" (Alesina & Ferrara (2002)).

If we look a bit further, trust have occupied many economists interest. Some of them have mentioned it in bargaining games. Mccabe, Rigdon & Smith (2007) studied a two-person bargaining games between trusters and non trusters and adapted the idea of population clustering. They showed that if cooperation exists, they will try to make it more robust and not get affected by defectors. Molm, Schaefer & Collett (2009) defined transactions costs and illustrated two forms of exchanges : reciprocal and negotiated. The first one is characterised by the absence of formal agreement, as for the second form, it is *secured*

5. Sometimes these mechanisms are referred to as moral hazard and adverse selection mechanism

by binding agreement. So, is trust a simple case of formal agreement ?

In fact, loyalty is not the main focus, but it is the first step for agents to stabilising some negotiation patterns. As well, the emergence of loyalty leads to price dispersion (Kirman & Vriend (2001)) (For pice dispersion see (Verboven (2008)). Kirman et al. (2008) showed that the bargaining activity is linked to the kind and the location of the business. Loyalty and bargaining get customers prices that are better than the average price. Their result was a contradiction of the study of Weisbuch et al. (2000). Brehm & Rahn (1997) argued that there is a mutual reinforcing between trust and social capital and that social capital has a stronger effect on trust that trust has on social capital and trust is an important component of the social capital that actors accumulate through their relationships to one other (Fukuyama (1995) and Paxton (1999)).

Theoretical and empirical studies showed that trust mixed with trustworthy behaviours among others reduces uncertainty, risk and costs. Other as Meidinger et al. (1999) reported that people trust each other when they know that trust will generate the maximum profit. Using an experimental method, Meidinger et al. (1999) established a precise measure for the agents behaviour that was used to identify trust. As a result to the investment game, 84% of people trust "in a certain way" other people. They showed that reciprocity and trust explain together the economic phenomena in an easiest way. Hence, trust is based on the "anticipation of the reciprocity behaviour". Moreover, Orléans (2000) introduced the economic theory of trust. He showed using the Nash Equilibrium, the difference between optimisation in a repeated game and in a one shot game. He presented the effect of reputation on the transactions (for the model of reputation with adverse selection see also Cabral (2005)).

Trust has today an important role in the economic theory. Lots of empirical studies are done to highlight it importance in economy. But the main problem in their studies was to identify and to measure trust.

As for Guiso et al. (2009), they studied bilateral trust between european countries. Trust is not affected by the characteristics of the country ; being trusted is also related to the cultural aspect such as religion, history, conflict, language, somatic and genetic distance. This idea was not totally supported by Alesina & Ferrara (2002). They showed that religious beliefs and ethnic origins do not significantly affect trust and that race appears as an important determinant of trust ; Therefore it is correlated to the community (heterogeneous or not) in which the individual lives (discrimination between minorities, women and blacks) and to its characteristics (income, education). Uslaner & Brown (2005) using data from the US states, showed that trust differ across countries and not across states (see also Holm & Danielson (2005) trust considerably differ between Sweden and Tanzania).

Berg et al. (1995) considered the role of trust in a two-person exchange in an investment game. They showed that people will risk some amount of money in order to gain trust and reciprocity in the exchange game. As for Glaeser, Laibson, Scheinkman & Soutter (2000), they measured trust and trustworthiness using experiments with monetary rewards. 196 persons played the experimental trust games. Their game is similar to the investment with imperfect contract. Trust is defined as the amount sent by the sender, and trustworthiness as the return share of the amount that the recipient receives. In summary, first they showed that past trusting behaviours influence whether someone is trusting. Second, individual characteristics as family status, social and interpersonal skill and charisma "strongly" affect trust.

In this thesis, trust is analysed as a way to diminish risk aversion, uncertainty and asymmetry of information between buyers and sellers. A study of the amount and the intensity of trust and its relation to the markets mechanisms are highlighted.

Faire confiance, c'est risquer certains aspects de son avenir en pariant sur la loyauté de la personne à laquelle on fait confiance

Canto-Sperber (1996)

2 Quantifying the differences between the auction and the negotiated submarket : the role of the structure of interactions

Creating a social science experiment is a complicated problem. Moreover the variables used and studied in these models are difficult to define. We therefore propose an interesting case to discuss. This paper compares the robustness and the nestedness of two submarkets (an auction and a negotiated submarkets) by studying a bipartite network formed by the interactions between buyers and sellers. We apply the tools of mutual ecosystems to study the largest fish market in France, Boulogne-sur-Mer, a market where these two structures coexist. We explore the microscopic interactions, that we believe, are at the origin of the observed regularities. This paper represents a continuity of an existing debate that consists in comparing the two structures : auction versus negotiated systems. On the basis of fidelity interactions, this paper shows that auction and negotiated submarkets are different.

0. A paper jointly written with Laura Hernandez and Annick Vignes is based on this chapter

2.1 Introduction

Which one dominates the other, centralised or decentralised structure ? An existing literature focusing on comparing from a theoretical and an empirical backgrounds the two different market designs : *"auction versus negotiated"*, attracted many attention. In terms of efficiency, this comparison emerged with the pioneer article of Grossman & Stiglitz (1976) [1]. In addition, Milgrom (1986) proved that centralised markets were more efficient than decentralised one. But the study of Goldberg (1977) and Manelli & Vincent (1995) suggested that negotiations patterns may be better than auctions. This wasn't in line with the result of Bajari et al. (2009) who gave credit to auction mechanisms. Moreover, Kirman et al. (2008) showed that profits on decentralised markets are higher than centralised one, unlike Bulow & Klemperer (1996) [2] and Milgrom (2004) who gave credits to centralised market that predominate the decentralised one.

However, there is no unique consensus on which all economists agree. This paper is an attempt to compare both structures considering their robustness and their nestedness. We believe that the results are more interesting when we compare both structures with the same conditions. The Boulogne-sur-Mer fish market, marked by the coexistence of a centralised and a decentralised mechanism, forms the perfect case for this comparison. The robustness and the nestedness measurement for this fish market is a way to evaluate the amount of information on both designs. The existing literature confirmed that the auction mechanisms are know as a structure where the information is centralised, whereas the negotiated is a market where the information is decentralised. This paper has an important goal, which is to show that the intensity of links created among buyers and sellers on this later, are an alternative for the lack of information.

1. Efficiency is explained by the price system that convey the necessary information to attain the Pareto optimal allocation of resources

2. Efficiency for them is explained by the best way, the most profitable one when it comes to selling a company

In this paper, to analyse and to compare both structures in terms of information, we apply the social network tools. The study of social networks and particularly bipartite ones got many attention and multiple ones were and are still given. This paper studies and presents a trading example. It includes agents from two different guilds (buyers and sellers) who interact daily and where hundreds of kilos are exchanged. The Boulogne-sur-Mer fish market can be described as a system that works through bipartite network where nodes are represented by the agents and links are the interactions between the agents from the two guilds. These interactions can be represented through a complex network. Even if the idea of complex systems is becoming important and various literatures attempted to characterise it, researchers did not agree on a brief definition of it. However, Ladyman, Lambert & Wiesner (2013) provided a list of necessary conditions in order to identify complexity. Moreover, in economics, complexity grabbed the attention of Kirman (2010), Hausmann & Hidalgo (2014), Arthur (2013) : *"Complexity economics builds from the proposition that the economy is not necessarily in equilibrium : economic agents (firms, consumers, investors) constantly change their actions and strategies in response to the outcome they mutually create. (...) We also see the economy not as something given and existing but forming from a constantly developing set of technological innovations, institutions, and arrangements that draw forth further innovations, institutions and arrangements".*

The aim of this paper is to trace a possible causal relationship between the market structure (negotiated and auction) and the system's nestedness. The nestedness of a system can be defined as follows : the more a system is nested, the more it is organised. This understanding, is however based on the notion of stability and robustness. The idea of stability and market robustness emerged and had particular attention in financial market after the crisis of 2008 and 2010. Economists tried to understand how markets function, but they neglect the market fragility, robustness and collapse. However, as Blume (2010) mentioned that economists did not totally ignore market design and market collapse ; the market structure remains important in economics even if many did not pay attention to it. The structure of market has been intensely studied for financial markets but there is no paradigm for understanding market robustness and collapse.

Nestedness analysis is one of the central topic in ecological systems [3]. Burgos, Ceva, Hernández, Perazzo, Devoto & Medan (2008) studied the market robustness of a biological system. Their study is done using bipartite networks, networks formed of two types of nodes and only nodes from different types are connected [4]. For the past few years, many studies were based on the complex networks theory to provide secrets and information about interactions between species and stability of mutualistic networks. The interactions mutual benefit between species in a community occupied many researchers interest as Bastolla, Fortuna, Pascual-Garcia, Ferrera, Luque & Bascompte (2009), Blume (2010), Ermann & Shepelyansky (2013), and Medan, Perazzo, Devoto, Burgos, Zimmermannd, Cevac & Delbuee (2007). The degree of tolerance to errors differs throughout complex systems ; many biological networks hold on after environmental damages, as so for communication networks after malfunctioning. In this paper, we will see if the robustness response is related to the market and to the network structures (auction and negotiated). Generally a robust system reflects if a system recovers quickly after an attack and does not break down easily. Hence, we are going to test whether centralised or decentralised structure is more robust or fragile (can collapse) after a removal of a buyer or a seller. We show if buyers-sellers relations on the Boulogne-sur-Mer fish market are similar to the ecological system as it is proved by the analysis of Ermann & Shepelyansky (2013) who explained that *countries and trade products have relations similar to those of plants and pollinators and that the world trade network is characterised by a high nestedness typical ecosystem*. The buyer-seller relations are defined using the notion of loyalty ; we believe that buyer-seller relations should

3. Nestedness became a subject with high interest, more than 300 papers were published in the last 14 years

4. For example on the labour market, a bipartite network is formed by the employers and the employees.

be more intense on the negotiated structure as agents interact unlike the auction structure. We provide a unified picture of a complex network between buyers and sellers throughout different market structures. This paper is organised as follows : first, a detailed explanation on how nestedness is interpreted in the ecological system is done in section 2.2. The Boulogne-sur-Mer fish market is introduced and tested in section 2.3 in order to analyse if robustness and nestedness differ throughout market designs. A loyalty index is introduced in section 2.4 and we conclude this paper in section 2.5.

2.2 The theoretical background : a measurement of heterogeneity

The method used in this paper to highlight the influence of the amount of information among two market structures is usually employed by ecologists. Recently, they tried to explore the robustness of mutualistic networks. However, understanding the robustness of networks is essential in this paper in order to show the importance of social links between agents and information availability. Here, we analytically quantify whether and to what extent market structure influences the network structure in the first place, because usually interactions between nodes are considered as random or neglected, and the robustness of this network in the second place.

New interests and researches on complex networks were born the last decade (see "*The Atlas of economic complexity*" by Hausmann & Hidalgo (2014). A complex network is a network whose structure is irregular and evolves in time. It focuses also on moving from an analysis of small networks to a system with thousands or millions of nodes (Boccalettia, Latora, Morenod, Chavez & Hwang (2006)). Two seminal papers lead this rush on complex network ; one paper by Watts & Strogatz (1998) and the other paper by Barabasi

& Bonabeau (2003). In what follows, we outline the meaning of the robustness and of the order of a network. Two methods are explained. The first one studies the order and the disorder of a network, therefore the amount of information is considered. The second method explains the robustness of a network. This paper analyses two different types of networks : a negotiated network where buyers and sellers interact and an auction network where interactions can be considered absent.

2.2.1 A measurement of a network nestedness

The measurement of order and disorder of a network is a way to evaluate the amount of information. As previously mentioned : the more the system is nested, the more it is organised. In general, using the ecological terms, a highly nested matrix is characterised by a low temperature and the system can be called "cold". Moreover, a non significant nested system is identified by the maximum entropy and hence the system will be considered "hot". In economics, because agents search for information on a decentralised market (the negotiated), they will intensify their links. Therefore this network should be more nested than a market where the information is centralised (the auction).

In the mid 1980s, Atmar and Patterson studied the hierarchical structure in species distributions and developed concepts and algorithms for exploring nested subsets of species in ecological communities. They introduced the idea of the network nestedness. *"In a perfectly "cold" system each species present in the assemblage would go extinct in turn as each species falls below its minimum sustainable population size, and that order would not change no matter how many times the experiment were repeated. But if the system temperature of the biogeographic event were raised, extinction order would concomitantly become less determined due to the increasing influence of random processes [...] System temperature becomes a relative measure of the disorder apparent in extinction order and* *will be defined to vary from 0 (completely replicable extinction order) to 100 (completely random extinction order)* (see Atmar & Patterson (1993)).

In general, to explain the system nestedness, a detailed definition for the presence-absence matrix should be given. The presence-absence matrices of the bipartite network provide two information : it reflects which species occur at which sites, and the relative hospitality [5] of sites to the species (see Patterson & Atmar (1995)). This adjacency matrix denotes the contact between the two nodes i and j of the bipartite network where the elements of the matrix $\in$ {0,1} (1 when a link is created between the two nodes, and 0 if else). Therefore, we can define two degree distributions of the projected graphs by summing all the $1's$. The method consists in reordering the vectors degree from the left (for the columns and for the rows of the matrix) [6] using the self-organising network model (SNM Method). After reordering the matrix, we draw a boundary line or the extinction curve also know as IPN (Isocline of Perfect Nestedness see Bascompte, Jordano, Melián & Olesen (2003)). A boundary line is the hypothetical line that separates the occupied area of the matrix (i.e., the upper-left corner of the matrix) from the unoccupied one. The distribution of unexpected presences and absences are the bases of the calculation. Presence is marked with a black square and absence with white square (see figure 2.1). White points above and to the left of the line, as well as the black points (presences) below and to the right of it, are termed by the unexpected. Every unexpected presence beyond the line has it own unexpected absence and *vice versa*. This method is the measurement of the dispersion of the wholes (the ones "presences" and the zeros "absences") from the median [7].

5. The hospitality of the site declines from the top to the bottom of the matrix
6. Reordering minimise the unexpectedness of occurrences
7. The distance of an unexpectedness presence or absence cell ij to the extinction threshold (boundary line) and parallel to the skew diagonal is called d_{ij}. The local unexpected u_{ij} is defined as : $u_{ij} = (\frac{d_{ij}}{D_{ij}})^2$ with D_{ij} as the length if the full line running for the jth row to the ith column, the matrix parallel to the skew-diagonal. The total unexpectedness U is summed over the rows and the columns. The temperature is equal to$T = kU$ where the constant k is $k = \frac{100}{U_{max}}$ (Patterson & Atmar (1995)).

In addition, perfect nestedness is achieved when all 1's are within a region of the matrix delimited by an extinction curve or isocline of perfect nestedness (Medan et al. (2007)). Temperature (T) is one measurement for the nestedness. Nested matrices are organised in a way that specialised species (the one that interact with one or few) are connected to the more generalist ones (the one that interacts with many). *"A nested pattern of interactions in which both generalists (species holding many interactions) and specialists (holding few interactions) tend to interact with generalists whereas specialist-to-specialist interactions are infrequent"* (Bascompte et al. (2003)). Moreover, Corso, de Araujo & de Almeida (2011) defined a highly nested matrix as the one that have a minimal mixing of zeros and ones. *The topmost point is judge to be the most hospitable [...] and the leftmost is whose niche requirements are most commonly and consistently met. In practice, it may be the most resistant to extinction, most prone to colonisation.*

Figure 2.1 (see Atmar & Patterson (1993)) represents different matrices denoted a, b, c and d with increasing T. We can easily see the difference between an organised matrix (cold) and a random matrix (hot) for equal fill.

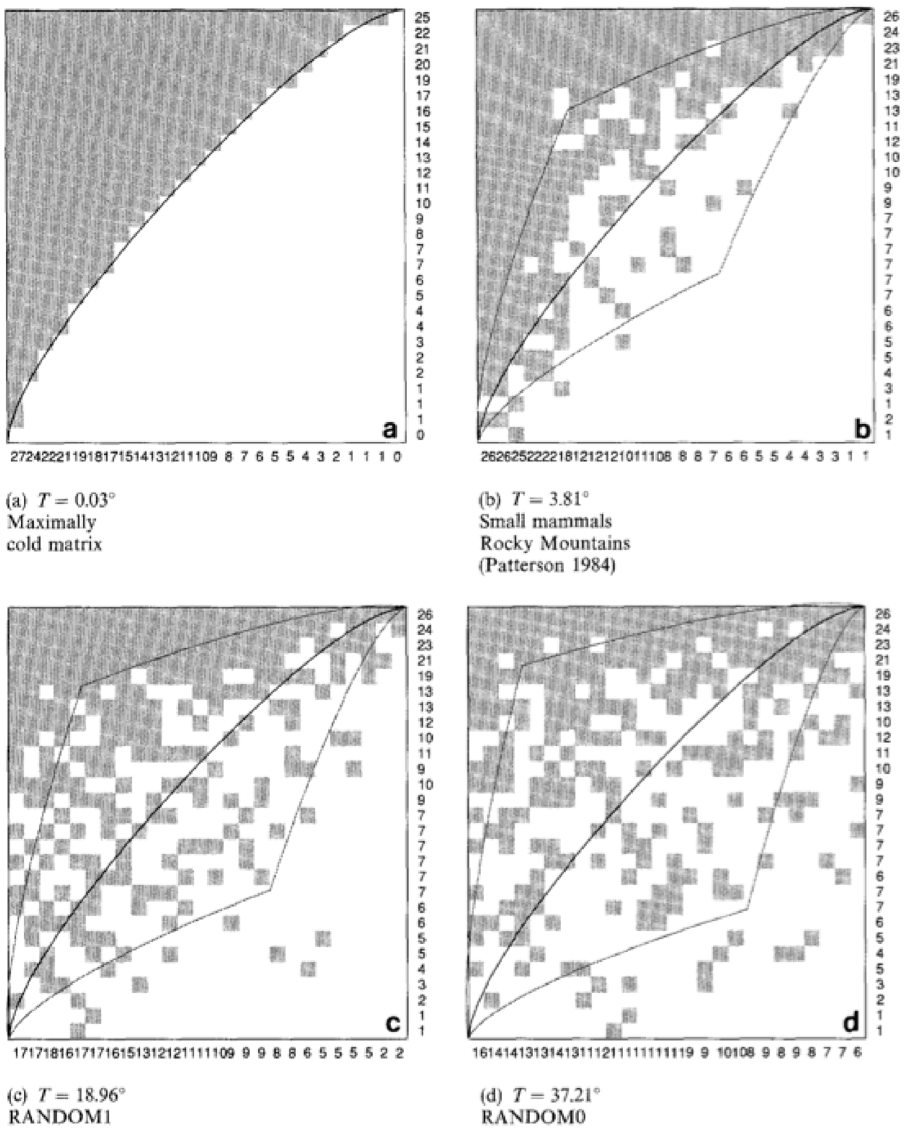


FIGURE 2.1 – Four different matrices for equal fill

But, this parameter is highly influenced by the size of the matrix and the density of the contact (the number of 1). Section 2.2.2 presents another metric. Instead of a metrical measurement, another alternative has been created. In what follows, an operational definition of the nesting coefficient is done.

2.2.2 An alternative measurement of the network robustness

An alternative to the Atmar and Paterson's measurement is introduced by Burgos et al. (2009). They put in place a nestedness coefficient in order to measure the nestedness degree of a network and hence the amount of information. In general, this coefficient describes the resistance of the system to an attack. The attack tolerance curve was introduced by Memmott, Waser & Price (2004). They simulated extinction by removing species from one guild and they observed which species from the other guild were left. Hence, this curve pictures the fraction of surviving species as a function of the fraction of extinct species (Burgos et al. (2009)). The system can suffer from random or targeted attacks. Figure 2.2 is example of different attack tolerance curves. Two extreme targeted strategies are noted : an attack from the smallest degree (open symbols), and an attack from the largest degree (solid symbols). The delimited area between the open curve and the solid curve explains the resistance of the system. The resistance of the system to the attack depends on its organisation. Hence the resistance of an auction system should be different from the resistance of a negotiated system. Because seising information is different on both designs, this method will show that the system resistance is linked to the amount of information. The problem can be resumed as follows :

- Negotiated submarket ⇒ information is decentralised ⇒ not the same information to all agents ⇒ the removal of an agent will have important effect ⇒ the number of strategic links is important ⇒ a more nested system ;
- Auction submarket ⇒ information is centralised ⇒ the same information to all agents ⇒ the removal of an agent will have less effect than on the negotiated submarket ⇒ the number of random links is important ⇒ a more random system.

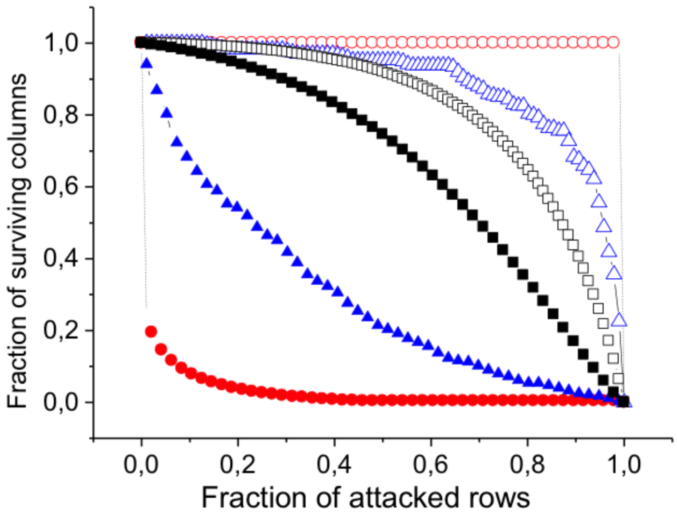


FIGURE 2.2 – An example of an attack tolerance curves

A perfectly nested system is presented by the red curves, as for the random system by the black curves. The blue curves are an example of a real matrix studied by Burgos et al. (2009). Their nesting coefficient is defined as follows :

$$N_{c(r)} = \frac{R^{-\to+}_{c(r)} - R^{+\to-}_{c(r)}}{1-\phi} \tag{2.1}$$

where $N = 1$ for a perfectly nested system and $N << 1$ for a random system and with c for a column and r for a row and where

$$R^{-\to+} = \int_0^1 f_s(f_k)\,\mathrm{d}f_k \tag{2.2}$$

with ϕ as the density of contacts, and R the area under the ATC. For a robust system, R approaches 1, the curve decreases slowly. Most of the species survive even if a large fraction of the species from the other guild are eliminated. For a fragile system, R is close to 0, the curve suddenly decreases. Most of the species lose their interactions when a small fraction of the species from the other guild are eliminated (see Burgos, Ceva, Perazzo, Devoto, Medan, Zimmermann & Delbue (2007)).

In this paper, these tools are applied in order to show that the centralised and the decentralised organisations represent dissimilarity on the nestedness level considering the social interactions. To sum up, the main goal of this paper is to highlight the importance of social links (when a lack of information is noted) on the robustness of this market. An answer for the following question is given :

Which structure is more organised : a centralised or a decentralised one ?

2.3 Application to an economic system : The Boulogne-sur-Mer fish market

The Boulogne-sur-Mer fish market is the right case to study this problem. Widely recognised for being the largest fish market in France, this market has its own specific organisation. It is marked by the coexistence of two selling mechanisms : an auction and a negotiated mechanism.

2.3.1 An heterogenous fish market : the data and stylised facts

The database provided by AgriMer France covers the one and a half year when both submarkets coexisted (April 2006 - December 2007). Detailed data about daily transactions in both submarkets are known. Date, species characteristics (id, size, presentation, quality), buyer's and seller's identities, trade mechanism (auction or negotiated), quantity and price are available (see figure 2.3).

	Date_vente	Bateau	Espece	Taille	Prsentation	Qulite	Type_transaction	Acheteur	Quantite	Prix_au_kilo	Montant
1	19/08/66	925601	33630	20	110	2	11	526	60	0.1	6
2	01/04/66	914099	24060	90	110	2	11	526	100	0.1	10
3	30/03/67	14124031	34090	20	110	2	11	543	558	0.15	83.7
4	14/04/67	14124031	34090	30	110	2	11	543	1578	0.15	236.7
5	20/04/67	14124031	34090	30	110	2	12	543	418	0.15	62.7
6	27/04/67	14124031	34090	30	110	2	12	543	1360	0.15	204
7	30/11/67	14124031	34090	30	110	2	12	543	140	0.15	21
8	20/12/67	14124031	32160	20	110	2	12	543	140	0.15	21
9	28/04/66	14124022	34090	30	110	2	11	543	1360	0.15	204
10	19/05/66	14124022	34090	30	110	2	12	543	20	0.15	3
11	10/11/66	14124022	34090	30	110	2	12	526	152	0.15	22.8
12	02/03/67	14124022	34090	30	110	2	12	543	620	0.15	93
13	14/04/67	14124022	34090	30	110	2	11	543	120	0.15	18
14	27/04/67	14124022	34090	30	110	2	11	543	120	0.15	18
15	20/12/67	14124022	34090	30	110	2	11	543	496	0.15	74.4
16	20/12/67	14124015	34090	30	110	2	11	543	100	0.15	15
17	20/12/67	14124015	34090	30	110	2	11	625	160	0.15	24
18	02/02/67	14124014	34090	30	110	2	12	558	100	0.15	15
19	02/02/67	14124014	34090	30	110	2	12	543	540	0.15	81
20	23/02/67	14124014	34090	30	110	2	12	526	570	0.15	85.5
21	03/03/67	14124014	34090	30	110	2	12	543	20	0.15	3
22	10/03/67	14124014	34090	30	110	2	12	543	229	0.15	34.35
23	22/04/66	14124013	34090	30	110	2	12	543	3320	0.15	498
24	22/04/66	14124013	34090	30	110	2	12	526	2820	0.15	423
25	06/05/66	14124013	34090	30	110	2	12	543	420	0.15	63

FIGURE 2.3 – An example of the Boulogne-Sur-Mer data base

208 sellers and 100 buyers visit the BsM fish market (see table 2.1). Daily, unlike the sellers, buyers can switch from one market to another (see appendix B.1 and B.2).

Not only the existence of this market is quite a paradoxe, but its stable coexistence remains nowadays a mystery. On the basis of the classic microeconomic theory, one of both mechanisms should have disappeared. But from April 2006, both mechanisms (auction and negotiated) coexist and this market is the most important fish market in France. Therefore, a detailed study for this market is done in this section in order to understand his structure. Nevertheless, one major problem had to be announced : this market is known by his heterogeneity. Why so ? Because in the first place, the good in question is "fish" and fish are perishable and heterogeneous. Moreover buyers and sellers are quite different. The following distributions are a way to represent this market heterogeneity. Figures 2.4, 2.5, and 2.6 picture the distributions from the buyers side and the sellers side in order to demonstrate this heterogeneity. More than half of the buyers come to the BsM fish market half of the time. This is not the case of the sellers ; the distribution is quite different. The peak of 160 reflect that 15% of the sellers came 160 days on this market (see Figure 2.4). This can be explained by the size of the boats (there are boats that go to the sea for a longer period than others).

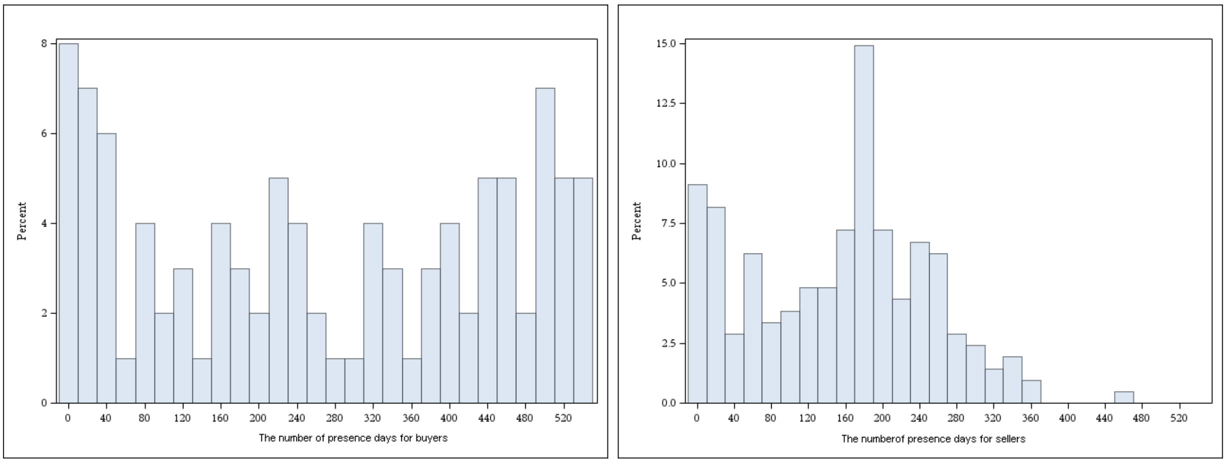


FIGURE 2.4 – The distribution of the number of the presence days for the buyers (left) and for the sellers (right) from April 2006 till December 2007

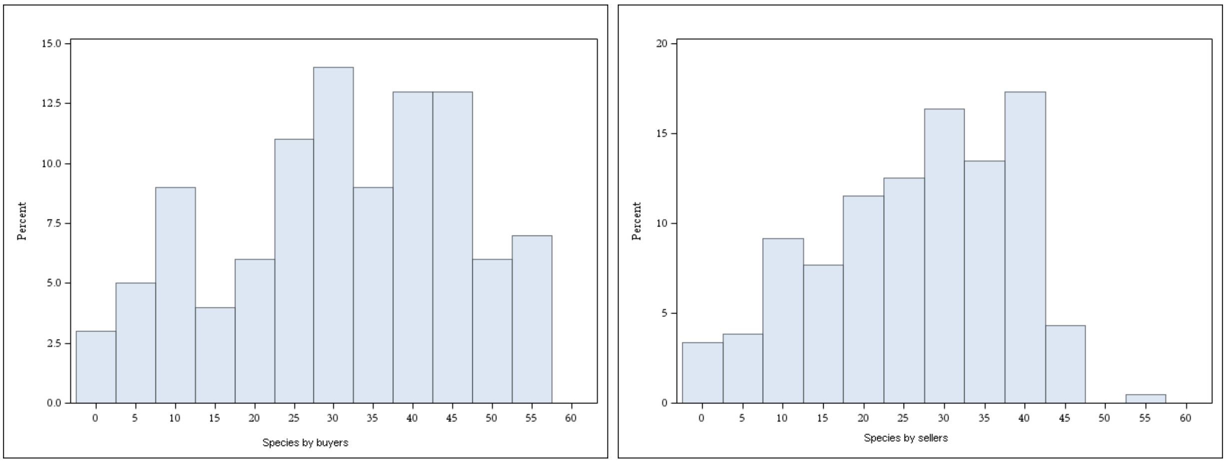


FIGURE 2.5 – The distribution of the number of species exchanged for the buyers (left) and for the sellers (right) from April 2006 till December 2007

Figure 2.5 represents the distribution for the number of distinct species bought and sold. Fifty percent of the buyers (sellers) bought (sold) more 32 (28) different kind of fish (see Figure 2.5). The last specificity of the agents is the quantity. The fish market is characterised by the diversity of the buyers and sellers' size (see Figure 2.6).

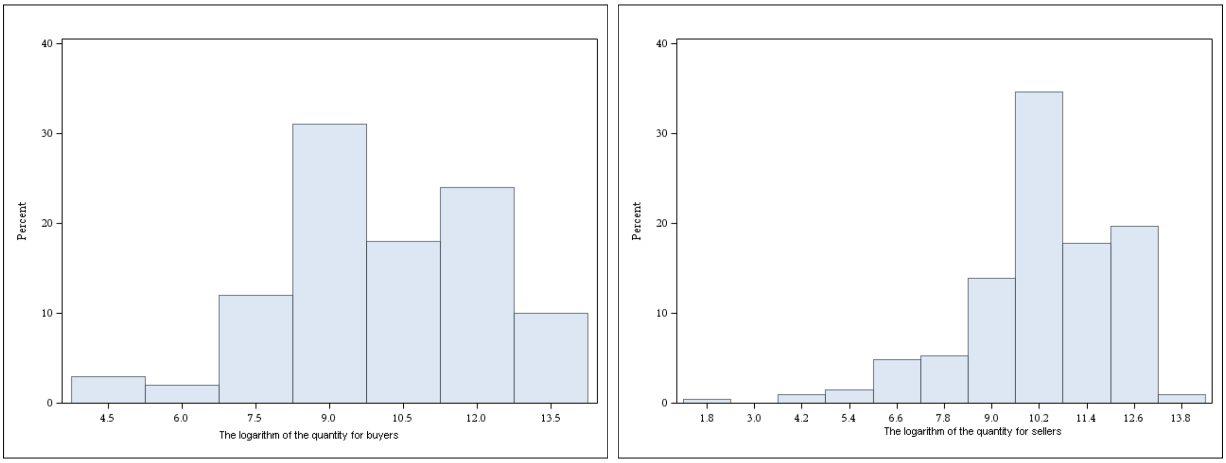


FIGURE 2.6 – The distribution of the quantity (logarithm) for the buyers (left) and for the sellers (right) from April 2006 till December 2007

In this paper, the Boulogne-sur-Mer fish market is introduced from a couple point of view. A couple is defined by a seller and a buyer connected by at least one interaction. Figure 2.3.1 represents the tree of the 11080 different couples. 10125 couples negotiated whereas 7842 couples auctioned. Among these couples, some of them are just nomadic and the others have particular relationship.

	Negotiated	Auction
Number of buyers	93	100
Number of sellers	207	195
Days the market is open	539	526
Number of formed couples	10125	7842
Number of possible couples	17836	16269

TABLE 2.1 – Data for the two submarkets over the all the period where both submarkets coexist

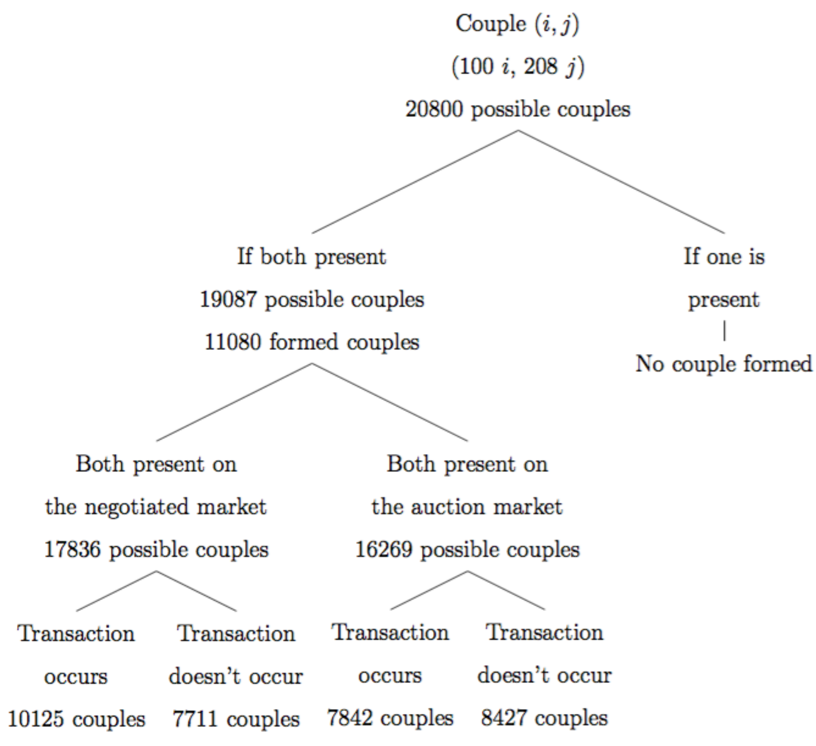


FIGURE 2.7 – The tree of the couple formation

In this paper, considering these couples we focused on the bipartite analysis of the Boulogne-sur-Mer fish market in order to prove the dissimilarities among both structures.

A distinction between these formed couples among structures is used to study the agents' behaviours and choices. We test this interactions' strategy using this fish market and discussing numerical results obtained with the Atmar and Patterson model and the robustness curves.

2.3.2 The bipartite nestedness approach of the fish market

This Boulogne-sur-Mer fish network can be drawn by an adjacency matrix where 100 buyers and 208 sellers are represented by the rows and the columns. This matrix is filled by *zeros* and *ones*. Denote the element of the matrix as :

$$K_{ij} = \begin{cases} 1 & \text{if a link is created between buyer } i \text{ and seller } j \\ 0 & \text{else} \end{cases} \tag{2.3}$$

for a giver buyer $i = 1, 2, ..., n$ and a given seller $j = 1, 2, ..., m$ i a given period (April 2006-December 2007). A link is defined by at least one transaction between the buyer i and the seller j.

The degree of buyers and sellers will be used in order to measure the nestedness of the different selling mechanisms. The difference between the buyers and the sellers of this market is hence measured by their degrees.

Denote the buyers' vector degree V_i where $V_i = [\eta_1, \eta_2 ... \eta_n]$ and with $i = 1...n$, and the sellers' vector degree V_j where $V_j = [\eta_1, \eta_2 ... \eta_m]$ and with $j = 1...m$. In this paper, consider the degree of buyer i on the negotiated or on the auction submarket as $\eta_i^{neg/auct} = \sum_{j=1}^{m} K_{ij}$ and the degree of seller j on the negotiated or the auction submarket as $\eta_j^{neg/auct} = \sum_{i=1}^{n} K_{ij}$. V_i and V_j represent respectively the y and the x axis of figure 2.8.

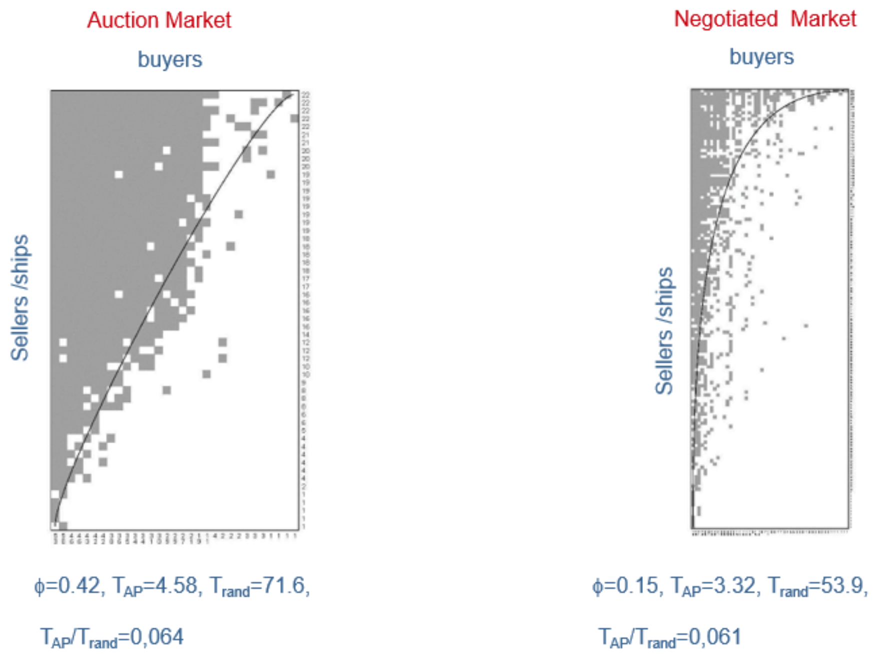


FIGURE 2.8 – Nestedness analysis of auction vs Negotiated - Autumn 2006

Figure 2.8 represents an example of the nestedness analysis of the fish market. Dissimilarities can be noted among both designs. The black points stand for a connection between the seller and the buyer whereas the white points symbolise the absence of a connection. In addition, the isocline of perfect nestdness (the black curve) shows different curvatures which confirms the difference between both structures.

Moreover, tables 2.2 and 2.3 show that for all the different seasons, the negotiated structure is marked by a lowest T. With these first results in hand, we can say that the negotiated submarket is more organised than the auction one. How can we explain this higher level of an organised structure ? Because information is not equally accessible to all the agents, "intensifying" the relation is the best solution. Therefore, these intense links that characterise the negotiated submarket could explain in the first place this difference between these two selling mechanisms and in the second place the alternative of the centralised information that exists on the auction submarket.

This negotiated structure is characterised by more generalist sellers who interact with generalist and specialist buyers whereas there are no specialist-specialist interactions. However the density of the matrix ϕ is not the same ; the analysis of Atmar and Patterson was considering as not the most faithful analysis because the matrices were not identical . Consequently the following ratio $\frac{T}{T_{rand}}$ is computed. T_{rand} stands for a random matrix that have the same characteristics (same size and density) of the studied matrix. Nevertheless, same results are obtained : $(\frac{T}{T_{rand}})_{neg} < (\frac{T}{T_{rand}})_{act}$. This nestedness approach confirms that the negotiated structure is more organised than the auction structure.

Matrix	Sellers (cols)	Buyers (rows)	Density (%)	T	Random T	T/T_{rand}
Autumn 2006	157	83	42.1	4.58	71.6	0.064
Autumn 2007	148	79	45.8	4.87	70.8	0.069
Winter 2007	145	83	43.3	5.3	71.3	0.074
Spring 2006	140	80	49.6	5.02	69	0.073
Spring 2007	134	75	54.4	5.15	67.9	0.076
Summer 2006	145	83	53.9	5.67	67.9	0.083
Summer 2007	155	76	43.8	6.42	71.8	0.089

Table 2.2 – Seasonal characteristics of the auction submarket

Matrix	Sellers (cols)	Buyers (rows)	Density (%)	T	Random T	T/T_{rand}
Autumn 2006	167	83	15.1	3.32	53.9	0.061
Autumn 2007	161	76	14.1	3.38	50.8	0.066
Winter 2007	159	79	14.2	3.75	51.8	0.072
Spring 2006	164	82	15.2	3.28	54.1	0061
Spring 2007	162	72	14.2	2.88	51.1	0.056
Summer 2006	159	79	15.9	4.36	55.3	0.079
Summer 2007	158	75	15.9	3.99	56.3	0.071

TABLE 2.3 – Seasonal characteristics of the negotiated submarket

When comparing the evolution of T with the seasons, we can see that the auction submarket become more messy when going from autumn till summer. Same results are for both years. This is not the case for the negotiated submarket. Both results are not the same and are not correlated with the matrix fill.

However, as previously mentioned the Atmar and Patterson's parameter is highly influenced by the size of the matrix and the density of the contacts, therefore in what follows, the Boulogne-sur-Mer market is tested using two alternative measurements : the attack tolerance curve and the nesting index.

2.3.3 The bipartite robustness approach of the fish market

As previously mentioned, our aim is to prove a difference between the two selling mechanisms. In order to do so, we will measure in this section the robustness of the network. Considering a bipartite network, we believe that the number random connections should be higher on the auction submarket. Therefore a removal of an agent (a seller or a buyer) should not have the same effect on the structure of both designs.

The analysis covers 4 consecutive Fridays of the year 2007 (April), one year after the coexistence of both designs. Agents (buyers and sellers) can be eliminated in two ways : (1) from the highest degree (full circle and square) and (2) from the lowest degree (open circle and squares) (see figure 2.9). The measurement of the network robustness is represented by the area between the two curves resulting from these two eliminations. We believe that when the information is decentralised, agents do not have the same information and have different behaviours therefore the delimited area between the two curves should be more important than the one formed on a market where the agents behaviour are similar and where agents hold the same information (a centralised market where the information is commun to all agents).

These first results of the ATC curves are quite encouraging. They prove that the networks that represented both structures are quite different. These results concern the data relative to the period of April 2007. Figure 2.9 shows the ATC curves for the auction (purple and green) and for the negotiated submarket (red and blue) from the buyer and from the seller side. The ATC are constructed from a daily adjacency matrix of the Boulogne-sur-Mer fish market. These curves represent for example the fraction of surviving buyers (the buyers who still have transactions) as a function of the fraction of eliminated sellers and *vice versa*. This ATC measures the robustness of a network face to different types of attacks.

As the area between the same color curves is in general larger for the negotiated structure, this later design is considered more nested. Moreover the curvature of this market (full squares) compared to the curvature of the auction structure (full circle) reflects a more nestedness structure.

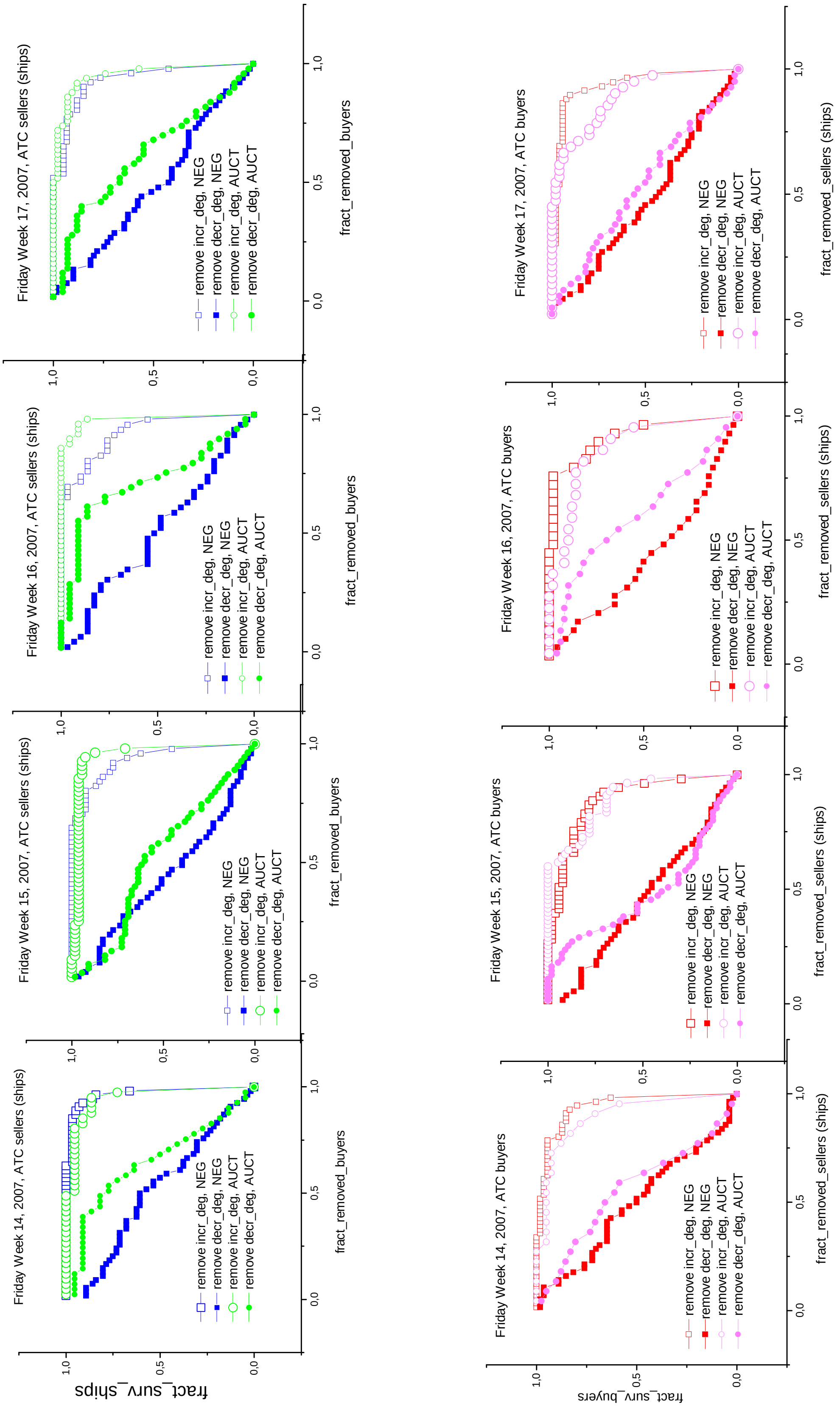


Figure 2.9 – The robustness using attack tolerance curves for auction and negotiated submarket - April 2007

Negotiated	0.525	0.470	0.560	0.508
Auction	0.441	0.506	0.370	0.406

TABLE 2.4 – The nestedness coefficient

Table 2.4 represents the nested coefficient for the auction and for the negotiated submarket for the Fridays of April 2007. The nested coefficient is defined as follows :

$$N = \frac{mN_r + nN_c}{m+n} \tag{2.4}$$

Face to different attacks, from the lowest degree and the highest degree, the nested coefficient for the rows and the columns of the matrix (buyers and sellers) are calculated. We have a higher nested coefficient on negotiated submarket ($N_{auct} < N_{neg}$). This explains a more organised structure for the negotiated design.

2.3.4 The degree and the strength distribution

This section considers a weighted bipartite network. The interaction pattern of a bipartite network is coded as an adjacency weighted matrix in which rows and columns are also labeled by sellers and buyers involved in the network. Denote the element of the matrix weighted by the interactions between j sellers and i buyers : $B_{i,j} \in N$. Each element of this matrix represents the number of days when i and j exchange (we label it also by the number of encounters). For each day t, K_{ijt} takes 1 value if one or more transactions occur between i and j, otherwise it is equal to 0. Hence, the element of this matrix $B_{i,j}$, that covers all the period of April 2006-December 2007, is $\sum_{t=1}^{T} K_{ijt}$ for every t=1...T.

But, the return frequency to the BsM market for buyers and sellers is not similar ; there are some buyers and sellers who never had the chance to be present the same day on the market. Hence there were no possibility of link's creation.
In order to distinguish these impossibility of interactions and the choice of non-interaction (represented by the 0 value in the matrix to identify couples who are present the same

day and choose not to interact), we symbolise these "impossibilities" by a -1 value in the matrix.

In order to verify the dissimilarity between both designs, we grow the distribution for the buyers an the sellers degree. Figures 2.10 and 2.11 represent respectively the buyer's and the seller's strength and degree. The degree gives an idea on the agent's diversification whereas the strength considers the repeated interactions. Figures 2.10 and 2.11 put in hand a first proof for the intensity of links and hence for loyalty (agents that interact with many few times, or agents that interact frequently with few).

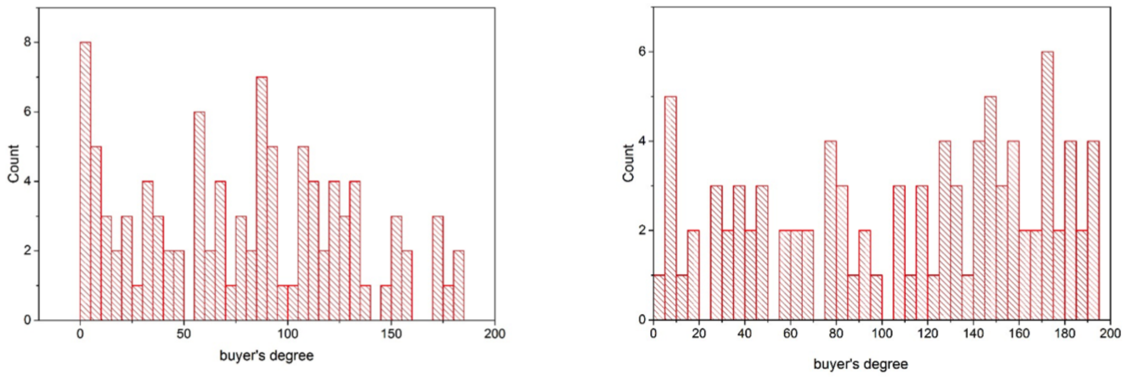


FIGURE 2.10 – The buyers degree on auction (left) and negotiated (right) submarkets

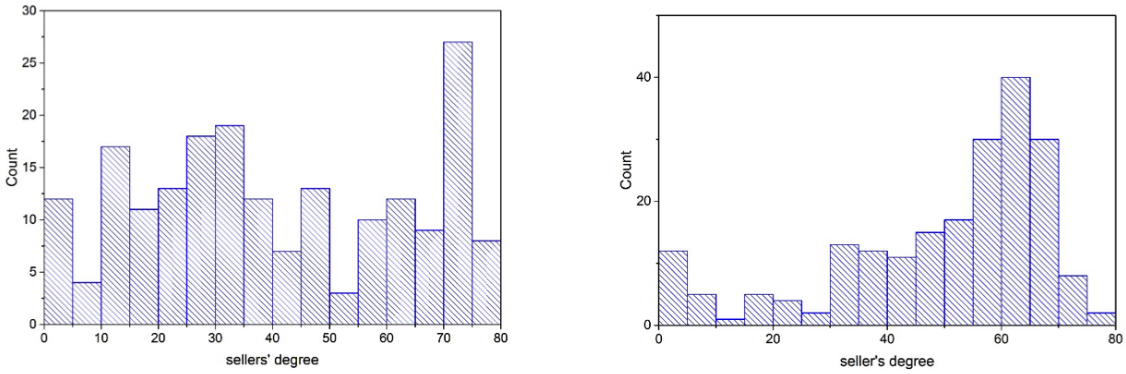


FIGURE 2.11 – The seller's degree on auction (left) and negotiated (right) submarkets

First results are quite interesting from the seller's side. The degree distributions are different. A more compatible with a uniform distribution[8] can be reported on auction submarket whereas a shifted distribution to the right on the negotiated submarket. Even if the seller's degree distribution is uniform on the auction submarket with a peak around 70, the strength's distribution tells a lot (see figure 2.13). There are few boats who have repeated transactions. This is not the case for the negotiated submarket. On this submarket, we can see a lot of boats who have a strength around 1 000, three times more than on the auction (figure 2.13). In order to have a clearer idea on the average of repeated contacts, we consider the worst case scenario. If we take the example of one of the sellers who had 1000 encounters, this seller is also one of those who had lots of clients, for example 50 (the mean of the degree). With this information in hand, we can say that each client has returned to his seller 20 times a period. However, if the same analysis is done for the auction submarket, one the 5 sellers who have 1000 encounters belong to the ones who sell to everyone (the peak of 70), what represents 14.3 encounters over all the period.

To sum up, the negotiated submarket is marked by close to 50 sellers who have a fidelity

8. taking into account the deviation above and under the straight line

of 20, whereas on the auction submarket only 5 sellers have a fidelity of 14.3 [9].

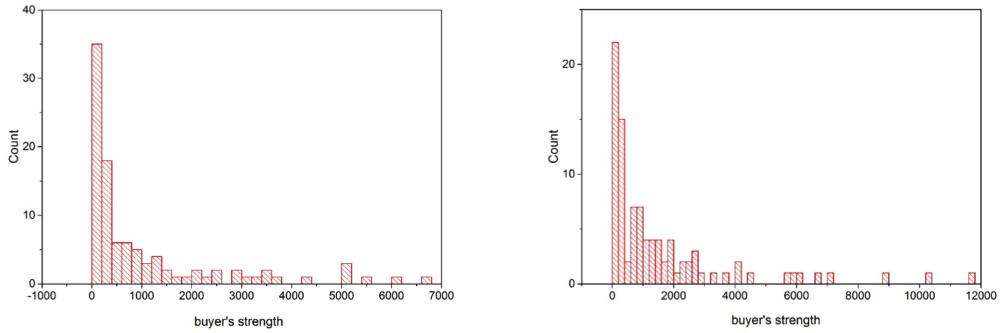


FIGURE 2.12 – The buyers strength on auction (left) and negotiated (right) submarkets

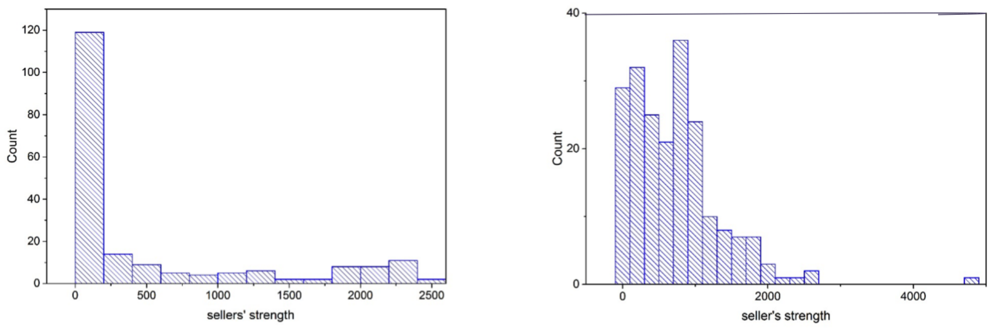


FIGURE 2.13 – The seller's strength on auction (left) and negotiated (right) submarkets

As for the buyers, the tail distribution is more important on the negotiated submarket, which means that this market is distinct by his actors who exchanged regularly with few sellers (W.C.S. 12 000/200= 60 times per seller over all the period and if they came frequently it is 60/300 days=2/10, two times every 10 days.)

Hence, this first network's analysis proves that there is something more than pure

9. All this becomes more meaningful considering that auction market is twice denser than negotiated market.

economic phenomena on this fish market. "Loyalty" can explain this contrast. In section 2.4, a loyalty index is defined .

2.4 The loyalty index

This loyalty index is a measurement of the intensity of interactions between a buyer i and a seller j. This measurement is explained using the weighted bipartite matrix B_{ij}. Equation 2.5 computed the number of encounters between i and j over the sum of the number of encounters for i and for j over all the period (2 is for normalisation).

$$F_{ij} = \frac{2B_{ij}}{s_i + s_j} \tag{2.5}$$

where

- the elements of the matrix B_{ij} represent the number of encounters between a buyer i and a seller j
- $s_i = \sum_{j=1}^{M} B_{ij}$ the strength of buyer i (weighted degree)
- $s_j = \sum_{i=1}^{N} B_{ij}$ the strength of seller j (weighted degree)

The loyalty index can take value between zero and one. Two extreme cases can be noted :

1. $F_{ij} = 1$ if a buyer i and a seller j only transact with each other during the studied period

2. $F_{ij} << 1$ if buyer i and seller j transact much less between them than with other agents during the studied period

The distributions of F_{ij} for both submarkets and the cumulative probabilities are represented in figure 2.14. At a first glance, both distributions are quit different. The tail of the negotiated distribution is larger which shows that more couples exchange very often. Moreover, the cumulative probabilities are distinguishable : a power low can be noted on the negotiated submarket unlike on the auction one. The cumulative distribution of the auction submarket have an inflection point whereas this is not the case on the negotiated submarket : the cumulative probabilities is a straight line. With this in hand, the negotiated submarket is marked by a higher level of loyalty. Loyalty therefore explains why the decentralised market is more organised. Agents meet and interact and intense bonds are created between the sellers and the buyers. On the auction submarket, a benchmark of the loyalty level can be noted. And because loyalty explains the decentralised designs, we understand more why a removal of an agents on this market will lead up to a collapsed market.

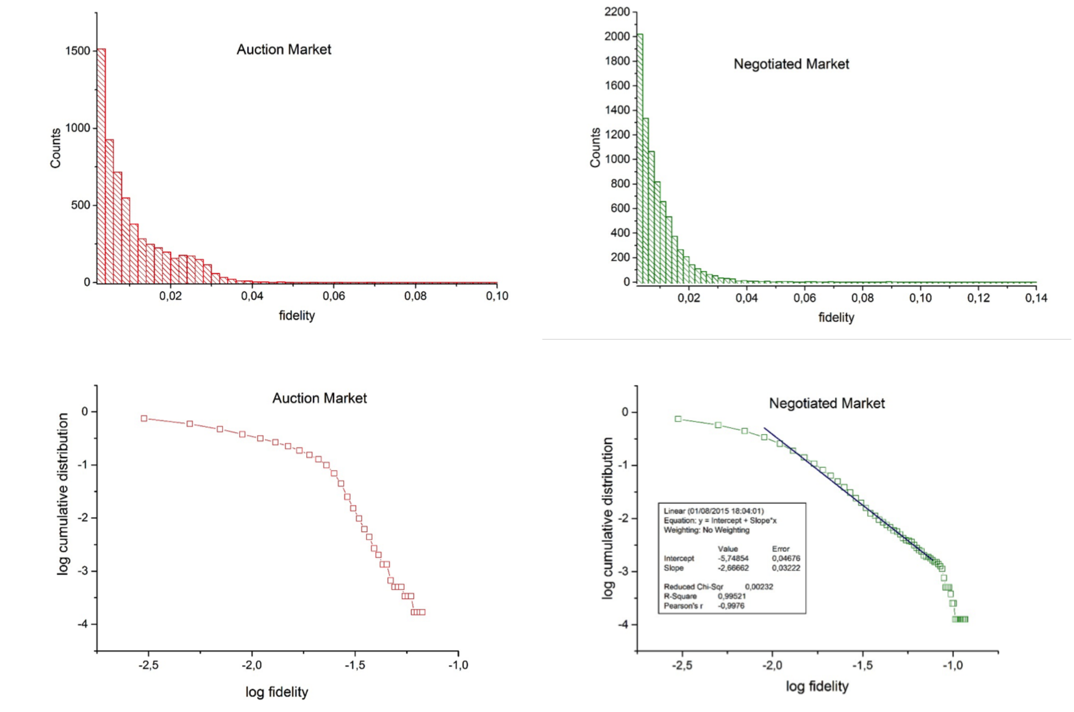


FIGURE 2.14 – The fidelity index on auction (left) and negotiated (right) submarkets

2.5 Conclusion

We used the tools and concepts developed to analyse mutualist ecosystems in order to investigate the pattern of relationships in a centralised versus a decentralised market. First results show that the negotiated submarket is sparser than the auction one. Moreover the robustness nesting index shows that the negotiated submarket is more nested than the auction one. In addition, the degree distribution are not power laws. This results is already seen in bipartite social systems. In spite of some cooperation mechanism in the negotiated submarket, the laws ruling this dynamics are different from the mutualist ecosystems. The strength distribution shows that the number of repeated transactions for the buyers has a larger tail in the negotiated market and the strength distribution of sellers is very different in both submarkets what reflects the "non choice" of the auction sellers.

A threshold of loyalty exists on the auction submarket whereas it is not the case on the negotiated one. Loyalty can be found on centralised market (one side loyalty). When sellers are not present, loyalty is explained by the name of the boat (the boat id on the screen). The non-existence of the loyalty threshold in the case of decentralised markets is explained by the facts that buyers and sellers are standing face to face. They interact together ! (two sides loyalty).

To sum up, the auction and the negotiated networks are different. On the decentralised market, link's creation is not totally random. Sellers are more present and interact more with their buyers. Therefore, loyalty and intense bonds explain this organisation. This selling mechanism will collapse faster than the centralised one, if an agent is removed. Why so ? Because loyalty are the basis of this design. Once we remove loyalty, this market will hardly "survive".

Les situations qui mettent en jeu la confiance constituent une sous-classe de celles impliquant le risque. Cependant, il existe une différence essentielle entre ces deux notions, puisque le risque peut renvoyer à des évènements auxquels se rattachent des agents non intentionnels, tandis que la confiance renvoie par essence à des relations stratégiques où la réussite des actions d'un agent dépend des actions d'un autre agent

Borlandi (2005)

3 How long does it take a buyer to find his match ? Trust in duration model

This article analyses trust creation from a buyer perspective among two different market designs (an auction and a negotiated structures). Our objective is to show that buyers act differently when it comes to trust. Even though measuring and modelling trust remain a problem, we believe that trust can be related to buyers' identity and to market's structure. This article differentiates between buyers using four different variables : the presence day, the quantity, the species and the number of connected sellers. After a segmentation of buyers in order to better understand their behaviour, the survival analysis model (non parametric and parametric) is used to analyse the transition time from a state to another. Each buyer is defined by two states : a *searching* state and *finding a match* or *trust* state. The analysis of the data of the Boulogne-sur-Mer fish market shows that small buyers are more loyal on decentralised market.

3.1 Introduction

We always thought that most markets, very often centralised one, are the most efficient because agents have the same information (Milgrom (1986) and Bulow & Klemperer (1996)). But this structure is not always the most suitable one. In a pioneer article, Grossman & Stiglitz (1976) concluded that without knowing the cost of operating a centralised information mechanism, no answer can be given whether centralised or decentralised design is the most efficient. There is an important literature focusing on comparing both structures (Moreno & Wooders (2010), Mansur & White (2007)). The market structure has a non negligible influence on the efficacy of resource allocation (Gode & Sunder (1997)). Mansur & White (2007) proved that "adopting a well-chosen market design wield improve market efficiency in areas where decentralised, bilateral practices prevail". The efficiency of unstructured bilateral markets is determined by how buyers and sellers are matched. It is difficult on these markets to observe and characterise participant's information. Before that, Milgrom (1986) and Bulow & Klemperer (1996) showed that to have efficiency, auctions are a solution and are a way to avoid risks (when bidders' signals are independent). But not many attention was given on the fact that if risk emerges, when somehow there is no signal for quality, "trust" will serve as a signal to decrease risk aversion. Bottazzi et al. (2005) suggested that markets rely also on agents interactions and relationship. Therefore, it becomes essential to understand the individual behaviour and the social interaction in order to explain the market itself at an aggregate level. We must analyse these interactions not only at an individual level but also at a market level. This paper is not targeted at showing a predominance of one structure over the other like many authors have done (auctions are more efficient than bilaterals or *vice versa*), but it will unveil that the market structure plays an important role in the creation of intense bonds between agents.

With an empirical analysis of the Boulogne-sur-Mer fish market, our study seeks not only to analyse the agents' choice and if they rely on trust, but also to understand if the market design matters when it come to trust creation. The Boulogne-sur-Mer fish market has its own specific organisation. It is marked by the coexistence of two submarkets : an auction and a negotiated one. Buyers and sellers can freely pick between both submarkets to exchange fish. Hence, when centralised and decentralised markets coexist, agents might prefer to go through decentralised market to cover from risk and uncertainty using relationships and interactions or through centralised market where it is easier to obtain information.

In order to define when trust is created and how links of trust are established, survival analysis is used. The link between trust creation and the market designs is then highlighted : "Duration analysis is a core subject of econometrics" (den Berg (2000)). It is used in labor economics, strikes duration, marriage duration and duration until death (see Kiefer (1988), Lillard (1993)). Indeed, duration models - also known as event history analysis (sociology), reliability analysis (engineering), failure time analysis (engineering), duration analysis (economics), and transition analysis (economics) - are used to reflect the timing until the event occurs [Allison (1995)]. They describe the transition time and the change from one state to another. Usually, they are used to measure how long an individual occupies and remains in a given state before moving to a different one. Hence the time interval between these two states can be calculated. Events like outbreak of wars, unemployment, earthquakes, automobile accidents, stock market crashes, collapsing cases, divorces are studied using duration analysis. Duration models are also used in the insurance models to estimate human life, in the unemployment models to estimate the length of time someone spends before finding a job, and in the medical fields to calculate the mortality time after injecting a random sample of rats for example with a carcinogenic substance. In a pioneer article, Bonnal & Fougère (1990) explained the duration of unemployment relying on demographic and socio-economic individual characteristics. Using a parametric model, they showed that these variables influence the probability to be hired. As for Aranki & Macchiarelli (2013), using a non-parametric and a semi-parametric models, they calculated the probability of retiring at a given age. Moreover, a recent study for Fougère, Golfier, Horny & Kremp (2013) showed the number of companies that disappeared after 2008's crisis but could have survived if the crisis did not happen. Fougère, Kamionka & Prieto (2010) showed that the "new french program" that assists unemployed people in job-search impact positively and significantly the return to employment. Duration models are therefore used in different domains, and there is still no real difference between the used techniques. Although they are used in many economics studies, they did not get many attention in social economics notably in *trust event*. But trust is not new in economics. During the last decade, many researchers have made empirical studies on trust.

The first study appeared in the survey of Rosenberg (1956). One question was asked : "Generally speaking, do you believe that most people can be trusted or can't you be too careful in dealing with people ?". After that many scholars tried to define trust and to estimate it. For example, Fehr (2009) relied on the behavioural definition of trust, where trust is not a special case of risk-taking but it is constructed on social preferences such as betrayal aversion. His definition of trust is tightly bonded to preferences and beliefs (as in Coleman (1990)). Fehr underlined the importance of risk, social preferences, and beliefs about other people's trustworthiness for trust behaviour. If we look a bit further, trust has occupied many economists interest. Some of them have mentioned it in bargaining games as Mccabe et al. (2007) [1]. In addition, Molm et al. (2009) showed that loyalty is not the main focus, but it is the first step for agents to stabilise some negotiation patterns. As well, the emergence of loyalty leads to price dispersion (Kirman & Vriend (2001)) (as for pice dispersion see (Verboven (2008)). Kirman et al. (2008) showed that loyalty and bargaining get customers prices that are better than the average price (see also Weisbuch et al. (2000)).

1. Mccabe et al. (2007) studied a two-person bargaining games between trusters and non trusters and adapted the idea of population clustering. They showed that if cooperation exists, they will try to make it more robust and not get affected by defectors

The contribution of this paper can be gauged under two perspectives. First, we provide for the first time, results for a survival analysis using trust. Second, we exploit the buyers differences and heterogeneity, throughout two different market designs, by quantifying their sizes and their characteristics. Nowadays, as trust remains an unresolved concern, it will be therefore tackled through the duration model within this article. Nevertheless, the following issues need to be pointed out, as the measurement of trust is complicated : Can trust be related to the idea of finding a match and be explained by the number of linked sellers ? How can we define it ? Can trust be differentiated throughout the buyers' type ? Starting with an empirical analysis on the Boulogne-sur-Mer fish market, we define trust and underline the buyers characteristics. The duration model will be tested, for the different categories of buyers, in order to show if "trust" is related to the buyer's identity.

The Boulogne-sur-Mer fish market is characterised by its agents heterogeneity. Around 100 buyers came frequently to the Boulogne-sur-Mer Fish market. Buyers are not identical, they do not have the same needs neither the same characteristics. Our original database does not procure information about them. Therefore, since buyers identity is not revealed, a wide analysis for buyers is employed in this paper. It will first characterise the different types of buyers according to the quantities (as quantity reflects the distribution channels : restaurant owner, supermarkets...), the species, the frequency of visiting the market and the number of connected sellers. We assume that these four variables reflect the buyers identity. Once this segmentation is done, trust is defined and then estimated using the survival analysis.
The situation can be pictured as follows : buyers on the Boulogne-sur-Mer fish market, search for the best combination of price-quantity. They have the possibility to choose among two different market designs : the auction submarket, where the information is centralised and common to all agents or the negotiated submarket, where the information is decentralised and where buyers are not fully informed about the market situation. Therefore, buyers are in a searching mode for a private information and for their match,

their favorite sellers (the best combination of price-quality). As prices are not displayed and there are no quality's signal, buyers are in a situation of imperfect information on the negotiated submarket. The game can be pictured as follows : first buyers search and visit many sellers, bargain over prices and quantities. Either they remain in a searching mode and switch from one seller to another ; or with time, they get into the circle of trust, find a match and choose their preferred sellers. While choosing sellers, we assume that buyers rely on trust (trust is reflected by the intensity of the link between buyer and seller). Hence, when moving from the search state to the trust state, the number of connected sellers should decrease with time. So, in order to explain trust in the duration model, we suppose that buyer's degree (the number of connected sellers to each buyer) is the most reasonable way.

This article is organised as follows : The Boulogne-sur-Mer fish market is introduced in section 3.2 and a segmentation for buyers is done. In section 3.3, the survival analysis is explained. In section 3.4, trust is explained and compared among the two market designs. In section 3.5, an application of a non-parametric model to the survival analysis on the Boulogne-sur-Mer fish market is discussed. In section 3.6, a parametric model using the buyer segmentation is done. The last section contains the concluding remarks.

3.2 Data and stylised facts

The Boulogne-sur-mer fish market, located in the North of France, is the most important fish market in terms of quantity. This market has a long history. It has operated over different systems. First, a decentralised structure has been put in place. Then after the E.U. instructors, the BsM fish market moved to an auction system. But agents on this market (buyers and sellers) refused this mechanism and voted for a market where both auction and negotiated coexist. Nowadays, this fish market is marked by the coexistence of these two designs.

200 boats and 100 buyers are registered in this market. The database covers the year and a half (2006-2007) where both submarkets coexist from Monday till Saturday. For each transaction, date, species and characteristics of the fish traded (size, presentation, quality), buyers and sellers id, type of trade mechanism (auction or negotiated), quantity exchanged and transaction price are known. As buyers identity is not listed, we aim to classify buyers. Buyers can be retailers, resellers as fish merchant, restaurant owners, supermarkets and high-volume stores, fishmongers or wholesale traders. They have different objectives and constraints (volume, species, budgets, available time to buy etc.) [2].

3.2.1 How to differentiate buyers in the market : the buyer main characteristics

In order to distinguish buyers, this original set of data can be further separated into quartiles. To do so, our N buyers are characterised by four variables : quantity, species, connected sellers and presence week.

Denote for each buyer i where $i = 1, 2, ..., N$ each week t, $t = 1, 2, ..., T$.

- Q_{it} as the quantity bought by buyer i week t
- S_{it} as the number of different species bought by buyer i week t
- η_{it} as the degree of buyer i, the number of connected sellers week t
- $\hat{T}_i$ as the total number of weeks buyer i transacts

We computed for each buyer on both submarkets the following ratios : A $=\frac{1}{N}\sum_{i=1}^{N}\frac{\sum_{t=1}^{T}Q_{it}}{\hat{T}_i}$ as the average quantity weekly traded per buyer, B $=\frac{1}{N}\sum_{i=1}^{N}\frac{\sum_{t=1}^{T}S_{it}}{\hat{T}_i}$ as the number of different species purchased in average weekly by buyer, C $=\frac{1}{N}\sum_{i=1}^{N}\frac{\sum_{t=1}^{T}\eta_{it}}{\hat{T}_i}$ as the average number of weekly connected sellers and D $=\frac{\sum_{i=1}^{N}\hat{T}_i}{N}$ as the average number of weeks a

2. For exemple, owner of expensive restaurant will search for high quality fish unlike cheap restaurants ; a fishmonger will want to finish early in the morning in order to be able to sell his fish and to open his store, while a transformer does not have a time constraint.

buyer i is present and trades on each submarket. By comparing these ratios between the auction and the negotiated submarkets, we differentiate buyers and analyse if buyers behave identically or not on both submarkets.

Ratio	Quantile	Min	25%	50%	75%	Max	Mean	Std
A	Negotiated	31.85	358.58	778.85	3 358.72	40 033.7	3 098.53	6 193.00
	Auction	8.83	183.03	523.97	2 919.42	22 439.87	2 368.85	4 245.00
B	Negotiated	1.00	3.78	6.83	12.00	26.38	8.71	6.09
	Auction	1.00	2.27	5.43	9.27	23.19	6.71	5.33
C	Negotiated	1.00	4.66	9.68	18.92	69.03	14.30	14.63
	Auction	1.00	2.58	6.89	15.17	47.76	10.83	11.36
D	Negotiated	3.00	44.00	81.00	91.00	93.00	65.51	31.28
	Auction	1.00	23.50	69.00	91.50	93.00	57.06	34.46

Note : Std indicates the standard deviation

Table 3.1 – Quantile of the quantity, species, connected sellers and week ratios (A, B, C and D) for negotiated and auction submarkets

Using the results of Table 3.1 and considering the weekly exchanged quantities, buyers can be divided to three groups : wholesale, medium and small buyers. 60% of the buyers are small ones ; 35% represents the medium and 5% the big ones (see appendix C.1). Moreover, Table 3.1 helps to identify buyers by the number of linked sellers. Buyers on the negotiated submarket have in average more connections weekly [3]. The Boulogne-sur-Mer fish market contains around 80 species of fish. These varieties can go from 0.1 euro per kilo to 42 euros per kilo. Buyers can also be differentiated throughout the type of fish they buy. They weekly purchased more species on the negotiated submarket at an aggregate level. Furthermore, buyers are more present on the negotiated submarket than on the auction

3. To note that the analysis is done over all the year and a half

one and more of them intended to visit more the negotiated submarket (25% of buyers visited 44 weeks the negotiated submarket and just 23 weeks the auction one).

As a difference in buyer's characteristics between submarkets can be noted, therefore their preference to one mechanism should be highlighted. To do so, we divided buyers into groups by comparing their presence on each submarket.

3.2.2 Segmentation of buyers

For each buyer, the following ratio is computed : F= $\frac{\hat{T}_i^{neg}}{\hat{T}_i^{auct}}$ where $\hat{T}_i^{auct}$ and $\hat{T}_i^{neg}$ are the number of weeks buyer i transacts on each submarket. A F value higher than 1 represents a preference for the negotiated submarket.

Ratio	Quantile	0%	5%	10%	25%	50%	75%	90%	95%	100%	Mean	Std
F	Estimate	0.00	0.00	0.92	0.989	1.00	1.12	1.95	2.50	5.00	1.20	0.78

TABLE 3.2 – The quantile of the buyer's preference for the auction or negotiated submarket (the number of weeks)

Buyers can be separated into three categories (Table 3.2). The first one is the category assigned to buyers who prefer the auction submarket, the second one is the one that contains buyers who are indifferent between both submarkets. The third category represents buyers for whom the negotiated submarket is prior.

Considering a threshold of 10% for the F's ratio, the three categories of buyers are defined as follows :

- category 1 : $\frac{\hat{T}_i^{neg}}{\hat{T}_i^{auct}} < 0.9$ are the ones who prefer to auction
- category 2 : $0.9 \leq \frac{\hat{T}_i^{neg}}{\hat{T}_i^{auct}} \leq 1.1$ are the ones who are indifferent
- category 3 : $\frac{\hat{T}_i^{neg}}{\hat{T}_i^{auct}} > 1.1$ are the ones who tend to negotiate

27% of buyers intended to visit the negotiated submarket, 4% went few times on the auction submarket and never visited the negotiated one, while 2% mainly visited the auction submarket. Around 61% of the buyers visited equally both submarkets.

Table 3.3 provides some description on how each category of buyers behaves once the submarket is chosen. We look at the three buyers categories for all the period when the market is open (93 weeks).

		Auction				Negotiated			
Category	N	Quantity Mean (Std)	Link Mean (Std)	Species Mean (Std)	Weeks Mean (Std)	Quantity Mean (Std)	Link Mean (Std)	Species Mean (Std)	Weeks Mean (Std)
(1) $\frac{T_i^{neg}}{T_i^{auct}} < 0.9$	9	1831 (2917.89)	2.6187 (2.24)	2 (1.174)	22.11 (30.86)	73 (147.33)	0.47 (0.95)	0.5 (1.23)	9.22 (22.89)
(2) $0.9 \leq \frac{T_i^{neg}}{T_i^{auct}} \leq 1.1$	65	3295.6 (4900)	15.51 (11.63)	9 (5.1)	73.4 (26.87)	4238.35 (7117.6)	18.68 (15.46)	11 (6.03)	73.95 (26.88)
(3) $\frac{T_i^{neg}}{T_i^{auct}} > 1.1$	26	237.88 (293.077)	1.98 (0.96)	2 (1.15)	28.31 (23.57)	461.7 (490.72)	4.274 (3.103)	4 (2.54)	46.27 (32.76)

Note : Std indicates the standard deviation

Table 3.3 – Descriptive statistics for the buyers variables by category on both submarkets

Category 1, the buyers who prefer the auction submarket, are the ones who visit 2.4 more times the auction structure and buy 25 times more quantities. They have 5.5 times more links and buy 4 times more species. This category can be labeled by the "big buyers", its also contains few "medium ones".

As for category 3, it represents buyers who came two times more on the negotiated submarket. These buyers purchase two times more quantities species and have even double number of links on their favorite submarket (the negotiated one). These 26 buyers are considered the "small ones". They buy around 400 kilos (see also Appendix C.1). We can say that 50% of the small buyers prefer to negotiate.

Finally, category 2, buyers who purchase equally on both submarkets, are more connected, and procure more quantities and species on the negotiated submarket than on the auction one. This category is mixed. It includes in the first place the "medium buyers" and in the second place the "small ones" (See appendix C.2 for detailed explanation about the buyers' behaviour on both submarkets according to their size).

The descriptive statistics suggest that buyers are not similar. Considering their size, they favour one submarket and have a different way of behaving among submarkets. Therefore in what follows, we establish an explanation for this difference. We believe that this dissimilarity is related to the intensity of links that buyers create, and how links are more intense on the negotiated submarket. The link measurement relies on trust. We use the duration model (the survival analysis) in order to prove who the market structure is the basis of all this dissimilarity.

3.3 Survival analysis : Terminology and notation

But *how long individuals remain in a certain state ?*

Does the transition time from a state to another can be influenced by market structure ? The aim of the following section is to calculate the transition time for each buyer and to show if it differs between submarkets. We will explain in details the duration model, the notation and then test the model using the data of Boulogne-sur-Mer fish market after defining the searching and the matching mode.

In every duration analysis, the analytic problem has to be describe. Three important points are then treated and defined ; first the initial situation, followed by the event of interest and finally the duration time as the outcome. The goal of the analysis is to estimate the time until a person get the event.

A simple way to picture the duration model is in three steps : First, all the observations should have an initial point in time. They survive for some length of times (also known as spells), then suddenly "risk" arises and a failing point is registered. Generally, in a survival analysis the outcome variable is "time until an event occurs". All the counted day, weeks, months and years from the beginning of the analysis until the event occurs, reflect the outcomes variable, thus the survival time.

Assume a random sample of N buyers entering the market and are in a searching process. We suppose that after a certain time, buyers will stop searching, find their match and get to the circle of trust. We record trust as the event and $\tilde{t}_i$ as the time until the event "find a match" occurs for buyer i. In order to simplify and to use the basic notation of the duration model in this section, we denote $\tilde{t}_i$ as the number of weeks of searching for the buyer i : $\tilde{t}_1, \tilde{t}_2, ..., \tilde{t}_N$. In practice, there are variations in the duration of spells of the searching mode from one individual to another.

Denote $\tilde{T}_i$>0 as the time measurement in a certain state, the random variable for a person's survival time (in our case the searching state). The duration of a state is then the difference between the starting date and the ending date of the state. But, for some individuals the date of spell termination is not observed, as well as the date of spell beginning, thus the survival time is not exactly calculated and censored data are therefore defined. The characteristics of this process lead to define a large classes of probability distributions for durations. In addition, specific probabilistic tools such as the survivor functions or hazard functions and risks, take a more decisive role in the analysis than the usual probability density because they can be easily interpreted.

$$Risk = \frac{\text{Chance that something happens}}{\text{Chance that it hasn't happened yet}} = \frac{P(Failure)}{P(Survival)} \tag{3.1}$$

A continuous random variable $\tilde{T}$ is characterised by a *cumulative distribution function* $F(\tilde{t})$, a *probability density function* $f(\tilde{t})$ and a *probability mass function* $P(\tilde{t})$.
We suppose : $P(\tilde{t}) = Pr(T = \tilde{t})$ with ($\tilde{t}$=1, 2, ...) as the *pmt*

and $F(\tilde{t})$= Pr(T $\leq \tilde{t}$) $= p(1) + p(2) + ... + p(\tilde{t})$ as the *cdf* the hazard function is :

$$h(\tilde{t}) = \Pr\ (\mathrm{T}{=}\tilde{t} \mid \mathrm{T} \geq \tilde{t}) = \frac{F(\tilde{t}) - F(\tilde{t}-1)}{1 - F(\tilde{t}-1)} \tag{3.2}$$

For $\tilde{t} > 1$

The hazard gives the probabilities of exit defined over the surviving population at each time (Arellano (1989)).

Harari-Kermadec (2008-2009) defined the hazard ratio as :

$$h(\tilde{t}) = \frac{f(\tilde{t})}{S(\tilde{t})} = \frac{\mathrm{d}\ \ln(\mathrm{S}(\tilde{t}))}{\mathrm{d}\tilde{t}} \tag{3.3}$$

Where $S(t) = 1 - F(t)$

The integrate hazard and the relation between the different functions can be noted as follow :

$$H(t) = \int_0^t h(u)\,\mathrm{d}u = -\int_0^t \frac{\mathrm{d}\ \ln(\mathrm{S(u)})}{du}\,\mathrm{d}u = -[ln\ \mathrm{S(u)}]_0^t = -ln\ \mathrm{S(t)} \tag{3.4}$$

With this in hand, let us provide some definitions.

A survival function $S(\tilde{t})$ gives the probability that a person survives longer than some specified time $\tilde{t}$, it gives survival probabilities for different values of $\tilde{t}$ and resumes information from survival data.

Theoretically, all the survival functions go down when $\tilde{t}$ increases. At the beginning of the study, $\tilde{t} = 0$, none of the individuals undergo the event, and when $\tilde{t}{=}\infty$, no individual survive and $S(\tilde{t})$ curves to zero. But, it is possible that not all individuals got the event. Hence $S(\tilde{t})$ might not end up at zero.

The hazard function $h(\tilde{t})$ gives the instantaneous potential per unit time for the event to occur, given that the individual has survived up to time $\tilde{t}$ at a given moment (Kleinbaum & Klein (2012)). The hazard function, known as conditional failure rate, is related to the failure and not the survival. In other words, it is the probability that an individual fails in the interval $[\tilde{t}, \tilde{t} + \Delta \tilde{t}]$ given that he survives up to time $\tilde{t}$. The hazard function is always positive and have no upper bound.

The average hazard rate is defined as the ratio between the total number of failures over the sum of the observed survival times. "The higher is the average hazard rate, the lower is the group's probability of surviving". A hazard ratio describes the relation between trust and survival time, after controlling for the appropriate covariates as an expression of a regression coefficient in the model.

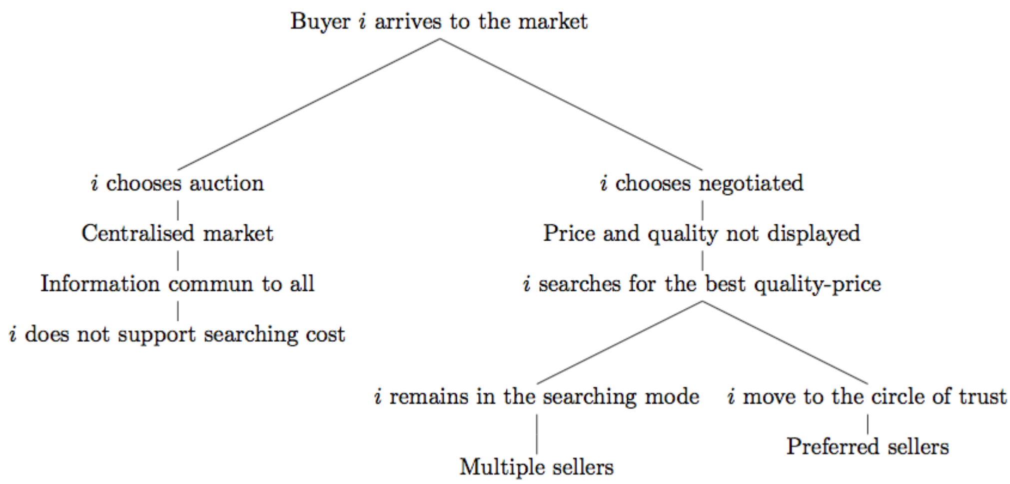
The difference between both function is that the hazard function measures instantaneous potential whereas the survival function is a cumulative measure over time. The hazard function can take many forms : increasing and decreasing Weibull, lognormal and exponential. Both functions are related, once one is know the second can be derived easily.

After having introduced and presented the duration model, we will test it using the Boulogne-sur-Mer fish Market in order to verify if the market structure has it influences on this duration model. To apply survival analysis, we need to know more than who trusts and who doesn't. We need to define and to measure trust in the first place and then to know when the changes in behaviour arose. That is, we should be able to fix the event in time and to know the exact time at which the event occur. The three steps of the duration model will then be defined as follow : the initial point in time as the searching mode, the risk as fund a match : trust and the spells as the duration between searching and entering the circle of trust.

3.4 Trust on the Boulogne-sur-Mer fish market

The aim of our study is to bring the light on the importance of the market structure on the intensity of the links and on the agent's behaviour. We believe that on the negotiated submarket, the transition time is lower than on auction and that the survival curve and the hazard rate are different (as trust is less intense on the auction submarket, the event will not certainly occur).

The Boulogne-sur-Mer fish market is build in a singular way and operates through an auction and a negotiated system. The focus of this analysis is at the buyer side. A study on how long it takes a buyer to find his match and to enter the circle of trust is considered. For some buyers the survival time is not exactly known for many reasons : first the study might ends without that the individual experiences the event, or he can be lost during the study and finally he can be withdraw from it. The situation can be pictured as below :



Buyers i are identified each week ($t_i = 1, 2...T_i$) by the number of linked sellers ($\eta_i = 1$, 2, ..., M), the quantity (Q_i) and the type of fishes (S_i) they weekly purchase. The influence of these variables on the degree of the buyers is worth looking at. Equation 3.5 shows that the buyer's degree is explained differently between submarkets.

$$\eta_i = \beta_1 + \beta_2 t_i + \beta_3 S_i + \beta_4 Q_i + \epsilon_i \tag{3.5}$$

with i=1... N

	Auction			Negotiated		
Parameter	Estimate	Std Error	Pr > ltl	Estimate	Std Error	Pr > ltl
Intercept	-0.709	0.224	.0016	3.149	0.333	<.0001
t_i	**0.0173**	0.003	<.0001	**-0.029**	0.004	<.0001
S_i	1.233	0.015	<.0001	1.081	0.019	<.0001
Q_i	0.001	0.0000	<.0001	0.001	0.0000	<.0001

TABLE 3.4 – Estimation results for the auction and the negotiated submarkets

We remark that on both submarkets, the number of links, known as the weekly buyer's degree, is influenced in the same way by all the explanatory variables except the week variable. It grows on auction but decreases on negotiated. So with time, the degree of the buyers decreases on the negotiated submarket. It is obvious that this is not the case on the auction. The results of the estimation are given in table 3.4. We observe significant coefficients for all the explanatory variables.

Multiple questions can be asked : can we relate this difference to (1) the quantity purchased on each submarket, (2) or the fact that buyers can move from a searching state to the circle of trust with time on the negotiated submarket ?

(1) Quantity per couple : We test if this contrast is related to the purchased quantities. The results of regression 3.5 show no difference for the quantity exchanged. Moreover, to better clarify this contrast, we consider the quantities exchanged weekly per couple on each submarket and its variability with time (49,5% of the quantity are sold on the auction submarket weekly).

The means of the quantity exchanged per couple weekly are similar on both submarket (224.3 kilos for the auction submarket and 225.2 for the negotiated one). No remarkable dissimilarity should be told. Hence the decreasing degree on negotiated submarket and the increasing one on auction submarket cannot be explained neither by the variability with time nor by the quantity exchanged in average weekly.

(2) The probability of return

As this dissimilarity cannot be related to the quantities exchanged, can the decreasing degree on the negotiated submarket explain the existence of a community of preferred sellers ? To clearly understand, one question should be answered : "Do buyers past decisions are going to influence their coming ones ?". The serial dependence between two periods is studied using the probabilities in order to better understand if the market structure can influence the buyers behaviours. In this model, what happened next depends only on the past state of the system and not on the sequence of events that preceded it. Therefore, we are interested in every two consecutive encounters and we study the probability for a buyer to transact two periods in a row with the same seller.

Each buyer i decides either to negotiate or to auction. He can freely pick among M sellers j ($j = 1, 2, ..., M$). Hence if they transact one or more products, a link L_{ij} is created between i and j and a couple (i, j) is formed. We denote S, a set of states $S = \{s_1, s_2\}$ where s_1 represents $L_{ij} = 1$ when one or more transactions occur otherwise s_2 is defined as follow $L_{ij} = 0$.

Hence the probability that a buyer i transacts with the seller j at the current state given that a transaction occurred between them at the past state, is counted. These probabilities are calculated for each couple on each submarket. A week period is considered for every state. We denote r as the ratio between the number of day i transacted with j over the number of days both agents are present each week. In other word, r is the percentage of days a couple transacts per week, it take values between [0,1] with r=1 when a buyer i and a seller j transact 6 days a week (they transacted everyday because the market is open 6 days a week) and 0 when the couple never transact.

Let :

- $Prob^{auct}(L_{ijt}^{r_t} = 1)$ as the probability for a buyer i to transact with a seller j at least r_t on the auction market
- $Prob^{neg}(L_{ijt}^{r_t} = 1)$ as the probability for a buyer i to transact with a seller j at least r_t on the negotiated market
- $Prob^{auct}(L_{ijt-1}^{r_{t-1}} = 1)$ as the probability for a buyer i to transact with a seller j at least r_{t-1} on the auction market
- $Prob^{neg}(L_{ijt-1}^{r_{t-1}} = 1)$ as the probability for a buyer i to transact with a seller j at least r_{t-1} on the negotiated market

$$Prob^{neg/auct}[(L_{ijt}^{r_t} = 1)|(L_{ijt-1}^{r_{t-1}} = 1)] = \frac{Prob^{neg/auct}[(L_{ijt-1}^{r_{t-1}} = 1) \cap (L_{ijt}^{r_t} = 1)]}{Prob(L_{ijt-1}^{r_{t-1}} = 1)} \tag{3.6}$$

$\forall\ t > 0$, $\forall$ i $\in$ (1, 2, ..., N) and $\forall$ j $\in$ (1, 2, ..., M) (See appendix C.4).

Equation 3.6 represents the probability that buyer i chooses seller j at least (r) of transacted days a week t, given that i had already chosen j at least r times a week $t-1$. For all the couples weekly formed on the auction and the negotiated submarkets, the upper probability (Equation 3.6) is then calculated. As can be seen, the probability to transact with the same seller the next period taking into account the past one, is higher on the negotiated than the auction submarket for all the given r (see Table 3.5).

r	25%	33%	50%	67%	75%
Auction	0.1413	0.1412	0.1316	0.081	0.077
Negotiated	0.1952	0.2001	0.1989	0.13	0.1129

Table 3.5 – The probability of transaction in two consecutive periods for both submarkets

It should be noted that if we want to examine the agents behaviour under the assumption that they can freely choose from whom to buy, we should look at the difference between the following probabilities.

$$\Delta Prob^{neg/auct} = P^{neg/auct}(L^{r_{t-1}}_{ijt-1} = 1) - Prob^{neg/auct}[(L^{r_t}_{ijt} = 1)|(L^{r_{t-1}}_{ijt-1} = 1)] \tag{3.7}$$

$\forall\ t > 0$, $\forall$ i $\in$ (1, 2, ..., N) and $\forall$ j $\in$ (1, 2, ..., M) .

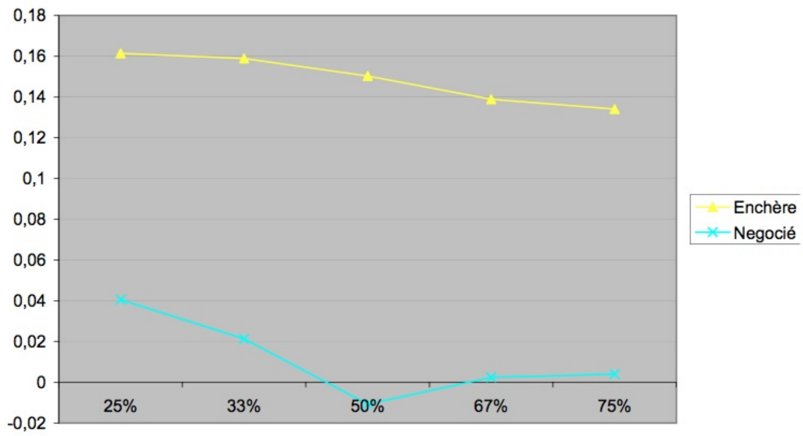


FIGURE 3.1 – A line plot for $\Delta P^{neg/auct}$

r	25%	33%	50%	67%	75%
Auction	0.1614	0.1589	0.1503	0.1389	0.1341
Negotiated	0.0406	0.0213	-0.0107	0.0024	0.00407

TABLE 3.6 – $\Delta P^{neg/auct}$ for all the given r

As shown in Table 3.6 and in Figure 3.1, ΔP^{neg} is always lower than ΔP^{auct} for all given r. It also takes negative values on the negotiated submarket. One explanation can be given, the probability that a buyer transacts with the same seller at time t given that a transact occurred at $t-1$ increases or is stable with the probability to transact with j

on the negotiated market. It decreases on the auction one. In aggregate terms, the market structure has different consequence on the probability of return to the same seller. It is obvious that this probability is more important on decentralised structure where agents get to meet and to negotiated.

In sum, the different values of β_4 in the regression can be explained as follows :

- The negative value on the negotiated submarket (1) is not related to the quantities exchanged (2) but it explains a community of preferred sellers. Therefore a changing in the behaviour of the buyers can be noted. The buyer moves from the searching process to the circle of trust. He learns from his past transactions and get to know his sellers.
- As for the positive value on the auction submarket, the following explanation can be done : as trust is not important on the auction submarket and agents do not interact, buyers buy from everyone to get what they need.

3.5 Non-parametric model

3.5.1 Survival Results for the whole market

Here, we propose to evaluate how the market structure have various impact on trust and on the link intensity. As already mentioned, each week $t = 1, 2, ..., T$, buyer i with $i = 1, 2, ..., N$ has the possibility to choose between M sellers $j = 1, 2, ..., M$. Once a transaction is occurred, a link is created and hence buyers can have several connected sellers (η_{it} as the number of connected sellers to buyer i the week t).

We proceed as follow : for each buyer i week t , we computed the below difference :

$$\frac{\eta_{it}}{M_t} - \frac{\sum_{i=1}^{N} \frac{\eta_{it}}{M_t}}{N}$$

where $\frac{\eta_{it}}{M_t}$ represents the buyer's degree over the number of sellers present on the market week t and $\frac{\sum_{i=1}^{N}\frac{\eta_{it}}{M_t}}{N}$ the market's average.

We consider that :

- $\frac{\eta_{it}}{M_t}$ - $\frac{\sum_{i=1}^{N}\frac{\eta_{it}}{M_t}}{N} > 0$ buyer i has more links than the market's average week t
- $\frac{\eta_{it}}{M_t}$ - $\frac{\sum_{i=1}^{N}\frac{\eta_{it}}{M_t}}{N} < 0$ buyer i has less links than the market's average week t
- $\frac{\eta_{it}}{M_t}$ - $\frac{\sum_{i=1}^{N}\frac{\eta_{it}}{M_t}}{N} = 0$ buyer i does not differ from the market's average week t.

The duration model consists in defining the event, an indicator variable that takes two values : (0) for censored data and (1) for buyers who get the event. We simplify the model by supposing that once a buyer trusts he is banished from the market, and so on when he is censored. We will try in a further study to re-integrate buyers who once they left the market because they get the event (trust), have the possibility to re-enter the market because of dishonesty.

But for now, the model is organised as follow. We assume that trust can grow with time and is related to the number of visited and connected sellers. A buyer finds his match once the number of his linked sellers is lower than the market average ($\frac{\eta_{it}}{M_t}$ - $\frac{\sum_{i=1}^{N}\frac{\eta_{it}}{M_t}}{N} < 0$). Therefore, buyer i moves from the searching mode to the circle of trust.

One major problem is to indicate precisely the time of trust [4]. That is why, we are interested in three consecutive periods.

$$\sum_{t}^{t+3}\frac{\eta_{it}}{M_t} - \frac{\sum_{i=1}^{N}\frac{\eta_{it}}{M_t}}{N} \tag{3.8}$$

We assume that if equation 3.8 [5] is negative, it explains that buyer i is getting more common with his connected sellers. He trusts the market and a change in his behaviour is be noted.

4. We assume that just a negative value can be related to a hazard phenomena but three consecutive ones could deny this assumption.
5. Equation 3.8 represents the sum for three consecutive periods.

The survival model will then be resumed as :

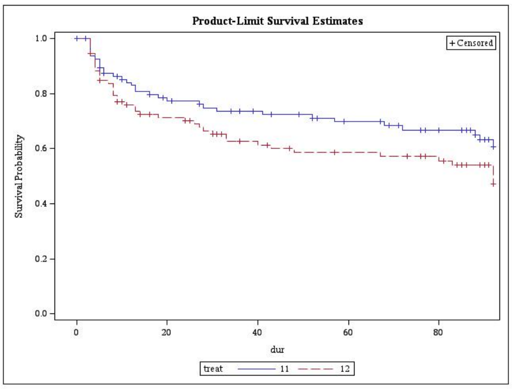
$$\sum_{t}^{t+3} \frac{\eta_{it}}{M_t} - \frac{\sum_{i=1}^{N} \frac{\eta_{it}}{M_t}}{N} \text{ is } \begin{cases} > 0 & \text{status} = 0 \\ < 0 & \text{status} = 1 \end{cases} \tag{3.9}$$

Table 3.7 is an example of a table of the survival time data for the buyers, where "dur" is the transition time and "status" represent if the event will eventually occur or not.

	dur	status
1	73	0
2	3	1
3	84	0
4	89	0
5	8	1
6	91	0
7	83	1
8	92	0
9	90	0
10	3	1
11	92	0
12	8	1
13	30	0
14	4	1
15	40	1

TABLE 3.7 – Example of a table

Figure 3.2 represents the Kaplan-Meier survival probability for both designs. The y axis denotes the percentage of the agents who have survived the events, while the x axis denotes the time (in our case the weeks). The little dashes show a censored buyer. The auction and the negotiated curves end up with a censored data point. As we can see, the survival probability is decreasing with the duration and it is lower on the negotiated submarket. A lower curve delineate that more buyers get the event on the negotiated submarket.
It appears that agents who are on auction submarket have a better survival rate than those who are on negotiated one.



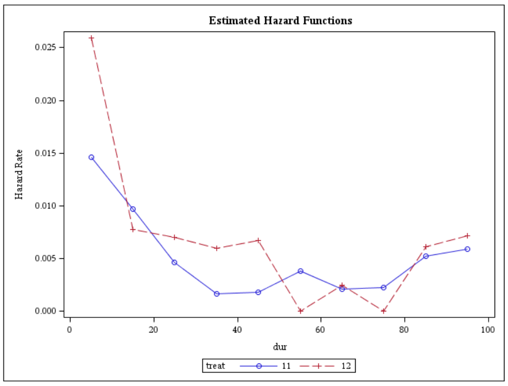


FIGURE 3.2 – Product - Limit Survival Estimate (left) and estimate hazard functions (right) on the negotiated (red line 12) and auction (blue line 11) submarkets

At time 0 everyone is surviving (figure 3.2) ; It seems that before 10 weeks, the two survival curves are virtually indistinguishable, with no visual effect of trust. The gap that develops after 10 weeks reflects the fact that buyers after this time period create intense links on the negotiated submarket that it cannot be seen on the auction one.

Test	Chi-Square	DF	Pr > Chi-Square
Log - Rank	2.31	1	0.13
Wilcoxon	2.189	1	0.14
-2Log (LR)	2.66	1	0.1

TABLE 3.8 – Test of Equality over strata

Table 3.8 test the equality over strata. The Wilcoxon tests if there is a significant difference in short-term between the groups (the two submarkets), while the Log-ranks tests whether a difference exists in a long-term. The hypotheses that are tested are : H_0 if the groups are equal and H_a if the groups are not equal. Table 3.8 shows that there is no significant differences between the two groups. But the Log-rank test and the Wilcoxon are invalid if the curves cross ! Hence the tests may not be able to detect a difference between the groups while this later one exists. The difference in our cases appears in the difference between the survival curves.

43% on the negotiated submarket and 32% on the auction submarket failed during the study. The "failed" word refers to the trusting behaviour. That is, loyal buyers on the negotiated submarket represent half of the population. The estimated time on the negotiated submarket is lower than on the auction one.

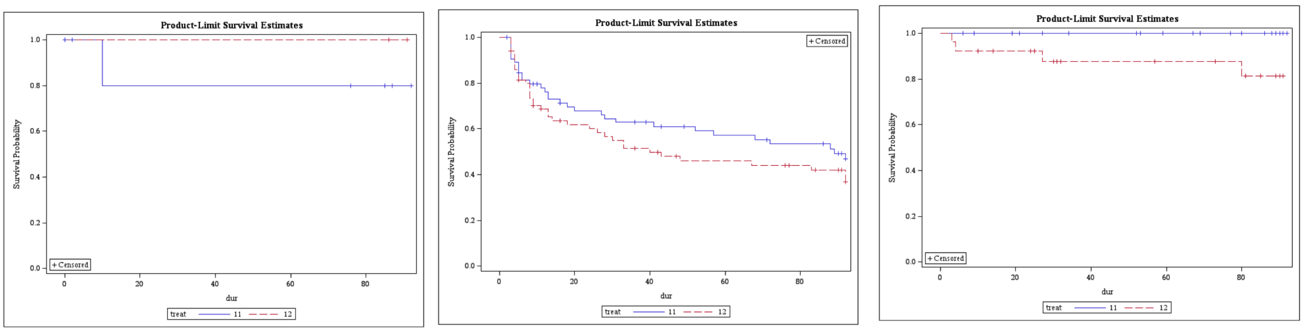
As with our survivor function (left figure 3.2), our hazard function is represented in figure right 3.2. Unlike the survival function, the hazard function does not have to start at 1 and to go down to zero, it can start from any value and take many directions over time (can decrease and increase as we can see). As already explained, the hazard function is related to the failure rate and not survival one what explain that the hazard curve for the negotiated submarket (red line) is for most of the time greater than auction's hazard one.
Similar to the survival analysis, the most important gap between the two hazard curves is around week 10. The curves also show a higher rate of failure on the negotiated submarket.

3.5.2 Survival results by buyers categories

In this subsection, we take a closer look at the duration model by the buyer's categories, in order to see, if in the first place we have different results for the 3 categories, and in the second place if the difference noted for the whole market is linked to one group of buyers more than the others.
Survival functions are drawn for the three categories : category 1 are the buyers who prefer auction submarket. This category contains the big and the medium buyers. Category 2 are the ones who are indifferent between submarkets, and the last category, the third one, are the buyers who have preferences to the negotiated submarket. It is represented by the small buyers.

Figure A - Category 1 : The survival curves for category 1 of buyers are similar as is it shown in the figure below. The statistical test in Table 3.9, as the Log-Rank and Wilcoxon prove that there is no significant difference in short-term as in long-term between the sub-markets. The value is 0.5 and it is not statically significant. This is confirmed by looking also at the survival curves that are identical. The gap between the two survival curves is related to just one buyer.

Result : Big and medium buyers who prefer auction submarket do not rely on trust. They behave in the same way on both submarket. Hence, that they similar : they have zero trust.



Category 1 Category 2 Category 3

Figure A : Survival functions on the negotiated (red line 12) and on the auction (blue line 11) submarkets.

	Cat 1			Cat 2			Cat 3		
Test	Chi-Square	DF	Pr>χ^2	Chi-Square	DF	Pr>χ^2	Chi-Square	DF	Pr>χ^2
Log rank	0.40	1	0.53	1.22	1	0.27	4.01	1	0.04
Wilcoxon	0.40	1	0.53	1.10	1	0.29	3.84	1	0.05
-2Log (LR)	0.81	1	0.37	1.71	1	0.19	5.81	1	0.01

TABLE 3.9 – Test of Equality over strata for the three categories

Figure A - Category 2 : The survival functions and the statistical tests for buyers who are indifferent between submarkets are represented by Figure A category 2 and table 3.9.

Both survival functions (auction and negotiated) decrease with time. But more buyers trust on the negotiated submarket than on the auction one. The statistical tests are invalid, because both curve cross till the tenth week [6]. But Figure A shows that both stratas are not the same and the dissimilarity is pictured by the gap between the curves.
Results : Category 2 contains all size of buyers. These buyers, after a 10 weeks period, once they are on the negotiated submarket will get to know their sellers. After that, we remark that the gap is stable. Buyers become loyal. Trust is more intense on the negotiated submarket.

Figure A - Category 3 : With table 3.9, they represent the survival probability over time and the test of equality over strata for the buyers who prefer the negotiated submarket. As seen the two curves are not the same. For this category, the survival curve for the auction submarket is a straight line. That reflects that this group of buyer who intended to visit negotiated submarket, choose this submarket because of trust. Furthermore, the statistical tests prove that both strata are not the same.
Result : Buyers who visit more the negotiated submarket have different behaviours on each design. Once they are on the auction submarket, their trust is zero. Once on the negotiated submarket, their trust is more important (red survival curve lower than the blue one).

3.6 Parametric model

We will deepen the statistical analysis in this section. We will test how trust duration depends on the three variables quantity, species and number of week interaction. "Let T_i be a random variable denoting the event for the ith individual in the sample, and let $x_{i1}, x_{i2}, ..., x_{ik}$ be the values of k covariates for the same individual. The AFT (accelerated Failure Time) model is then" : (Allison (1995))

6. There a difference between two lines that cross and two lines that are merged, coincident lines

$$LogT_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} ... + \beta_k x_{ik} + \sigma\epsilon_i \tag{3.10}$$

where ϵ_i is the random disturbance term, and β_0, ... β_K and σ are parameters to be estimated.

On the Fish market, we concentrate on the buyers behaviour because we believe that buyers characteristics have their influence on trust. Hence, the survival model can be written as :

$$LogT_i = \beta_0 + \beta_1 \frac{\sum_{t=1}^{T} Q_{it}}{\hat{T}_i} + \beta_2 \frac{\sum_{t=1}^{T} S_{it}}{\hat{T}_i} + \beta_3 \frac{\sum_{j=1}^{M} \hat{T}_{ij}}{\hat{M}_i} + \sigma\epsilon_i \tag{3.11}$$

where for each buyer i $(i = 1, 2, ..., N)$ and for each week t, $(t = 1, 2, ..., T)$ we denote :

- $\frac{\sum_{t=1}^{T} Q_{it}}{\hat{T}_i}$ as the average quantity weekly traded per buyer i
- $\frac{\sum_{t=1}^{T} S_{it}}{\hat{T}_i}$ as the number of distinct species purchased in average weekly by buyer i
- $\frac{\sum_{j=1}^{M} \hat{T}_{ij}}{\hat{M}_i}$ as the number of weeks a buyer i traded in average with seller j

These buyers variables are used to model the parametric estimation for duration analysis.

3.6.1 Survival results for the whole market

In what follows, the parametric tests are done for the whole market. The obtained results are in the line with the non-parametric model. They underpin the same outcome as section 3.5.

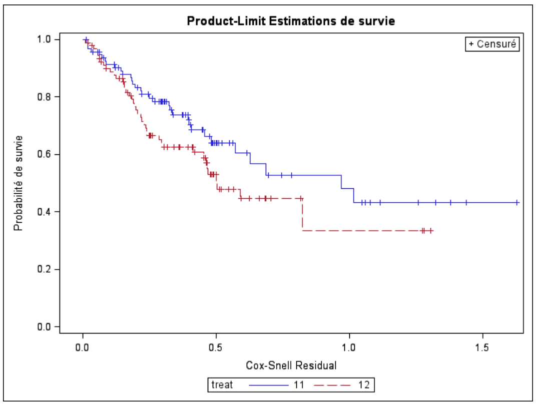


FIGURE 3.3 – Survival functions for the whole market on the negotiated (red line 12) and auction (blue line 11) submarkets

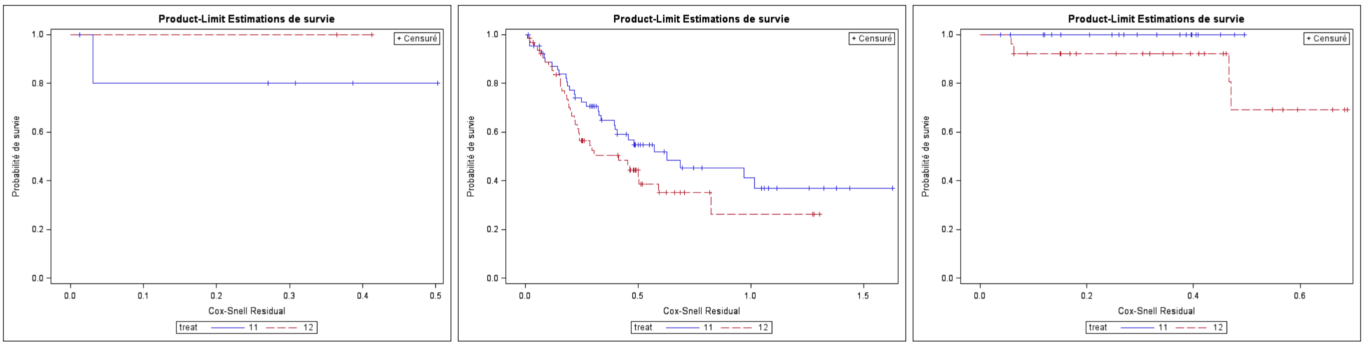
Test	Chi-Square	DF	Pr > Chi-Square
Log - Rank	2.55	1	0.11
Wilcoxon	2.54	1	0.11
-2Log (LR)	3.29	1	**0.06**

TABLE 3.10 – Test of Equality over strata for the whole market

The outcome of the experience in section 3.6 underlines that on the negotiated submarket, buyers have one and only dominant strategy : trust. On the auction submarket, two mixed strategies exist. Trust on the negotiated submarket can be compared to a disease. Once the disease is spread, it will attack at a fast rate most of the population. This effect can be seen in the first part of the curve. It decreases at a fast rate. The second part of the curve decreases at a slower rate. One explanation can be given. Let us consider an infected population. The population that was not affected by the disease earlier has a slight chance of suffering from it at a future time. Their immune system get stronger. This is the case of the buyers present on the negotiated submarket when it comes to trust.

3.6.2 Survival results by buyers categories

Figure B pictures the survival curves for all the three categories using the log-normal test for the parametric model of trust. For the buyers who visit more the auction submarket, no difference between the stratas can be noted. The statistical tests in table 3.11 show no significant difference between the two groups (the red and the blue curves). As for the ones who are indifferent between both submarket, statistical results and both curves prove that both stratas are not similar (Figure B and table 3.11). Moreover, buyers who visit more negotiated submarket, do not have the same behaviour. They behave differently when it come to trust (Figure B and table 3.11).



Category 1 Category 2 Category 3

Figure B : Survival functions for the three categories on the negotiated (red line 12) and on the auction (blue line 11) submarkets.

	Cat 1			Cat 2			Cat 3		
Test	Chi-Square	DF	Pr>χ^2	Chi-Square	DF	Pr>χ^2	Chi-Square	DF	Pr>χ^2
Log rank	0.40	1	0.53	2.32	1	0.12	2.32	1	0.12
Wilcoxon	0.40	1	0.53	2.19	1	0.13	2.15	1	0.14
-2Log (LR)	0.83	1	0.36	3.49	1	0.06*	4.91	1	0.02*

TABLE 3.11 – Test of Equality over strata for the three categories

3.7 Conclusion

This article analysed the link between the market structure and trust on the Boulogne-sur-Mer fish market. This research is an attempt to represent at a buyer level, a survival model. We divided buyers into categories and used these categories in the survival model. This paper showed that the market structure influences the time transition between the searching mode and the trust mode. Nevertheless, buyers on the Boulogne-sur-Mer fish market are different. There are small buyers, wholesale or medium ones. There are also buyers who prefer auction structure, negotiated or are indifferent among the two structures. Hence, buyers have different preferences for each submarket. Therefore it was interesting to see if buyers preferences and identities can affect trust between agents throughout different market designs.

The first results affirm that among submarkets buyers behaviours differ and they are different when it comes to trust. This is proved by the survival and the hazard curves that represent differences. In addition, different curves are pictured for the different categories. Buyers who visit more auction market have zero trust and "trust" is more important on negotiated submarket. Moreover, these trustee buyers, who characterise this submarket, intended and choose to negotiate more.

The duration model gives different results for the different categories of buyers on each submarket. Buyers who visit more the negotiated submarket trust more. As for the buyers who intended to visit more the auction submarket, they do not rely on trust while acquiring goods. Finally, buyers who are indifferent between both submarkets, are not similar at the trust level. A higher level of trust exists for this last category on the negotiated submarket than on the auction one. But an important point need also to be pointed out. Trust was found for this last category on the auction submarket. This can be explained by the fact that the boat-id is known by the buyers on the auction submarket. Therefore trust can be linked to the "boat-name". Particularly, when comparing with the bilateral market, sellers are not present, they have no choice (what can reduce trust level).

On reconnait généralement d'une confiance bien placée rend les transactions plus efficaces puisque les agents économisent les coûts engendré par les mesures de contrôles et de coercition

Borlandi (2005)

4 To trust or to bid : an empirical analysis of social relationships on a fish market

This article analyses the influence of trust on the functioning of a fish market, where agents can choose between bidding or exchanging through bilateral transactions. Even if it is well accepted in economy that trust plays an important role in transactions, its definition and its measurement stay, as far as we know, very elusive. Starting from the empirical analysis of the Boulogne-sur-Mer fish market, a market where people have the choice between trading through auctions or bilateral exchanges, we show how the social networks structure differ between the auction market and the bilateral one. We then propose a measurement of trust, based on the dynamics of agents encounters. We bring into the light that, when the transaction links on the auction market reflects the economic constraints of the partners, the relationships on the bilateral market depend on something more. Clearly, the bilateral transactions result from economics and non economics determinants.

0. A paper jointly written with Sylvain Mignot and Annick Vignes is based on this chapter

4.1 Introduction

It is actually largely accepted that markets need suitable institutions to be efficient and a huge literature has tried to design the "right" institutions. As well summarised by Milgrom (2004), the idea of auction markets more efficient than the decentralized ones has been largely developed at the end of the 20th century. Nevertheless, a more recent literature tends to suggest that the conditions of dominance depend on something more than simple price formation mechanisms. Clearly, the agents interactions, the structure of the social network and the consequence of the goods characteristics on agents' behavior influence the market outcomes.

Starting with the empirical analysis of a particular fish market (the Boulogne s/mer fish market), our study seeks to underline the role of social interactions on the dynamics of transactions. Because this market presents a particular organization (co-existence of an auction market and a bilateral one), it allows to evaluate the influence of social networks on the market outcomes. The idea that networks can influence the markets functioning is not new in economics. Kirman & Vignes (1990), Kranton & Minehart (2000) or Kranton & Minehart (2001) show how on certain markets, with a high level of uncertainty on the goods exchanged, linking is essential for transacting. The place occupied by an agent in the network (in terms of centrality for example) greatly influences its economic activity, as shown by Corominas-Bosch (2004) and Vignes & Etienne (2011)) or Fafchamps, Ductor, Goyal & Leij (2013).

This article yearns to look at the emergence and the stability of social links in a market : the fundamental hypothesis of our study is that trust between agents will influence the price of their transactions. In a former article, Milgrom, North & R.Weingast (1990) show that, in the case of repeatedly trading relationship, gains are possible when there is cooperation. The authors underline that by establishing a continuing relationship, individuals ensure one other's honest behaviour : agents benefit more by cooperating and then honesty becomes a necessary condition in trading relationship. Cooperating can be a dominant strategy, if there exists a credible threat and this threat could be the disappearance of trust (which corresponds to a come back to the non cooperative game).

In recent years, social scientists have claimed that trust plays an important role in transactions, as a keystone for cooperation. Trust mixed with trustworthy behaviours turn out to be crucial for reducing uncertainty (*cf.* Guiso, Sapienza & Zingales (2008)), risk (*cf.* Mccabe et al. (2007)) and costs (*cf.* Meidinger et al. (1999)). However, as Fehr (2009) remarks, the measurement and the definition of trust seem to be not fully settled, despite its proposed importance. Moreover, its emergence and the identification of its exact role in economic interactions stay elusive. Does trust come from good institutions ? Or does it help to reinforce the existing institutions ? In what follows, we postulate that trust emerges in a repeated game (or market) when two agents trade continuously together in a competitive environment : we show that this phenomenon is particularly important on the negotiated market, where the information is not centralised and where there exists no signal of information concerning the quality of the goods.

The question we ask here is how to measure the influence of trust on the dynamic of a market exchanges. A fundamental hypothesis of our study is that trust between agents will influence the price of their transactions. We define the level of trust between two persons by the number of encounters (number of days two persons traded together), relative to the number of encounters the same persons would done at random. The more two persons exchange together, the higher the level of trust is. Considering the market through the graph of transactions, we propose an original trust index based on repeated encounters between buyers and sellers and empirically estimated from the Boulogne s/mer trade network : this allows us to distinguish between the random encounters and the ones coming from trust relations. We then compare the two "trust networks" (auction and bilateral ones)and bring into light that on the auctions, links between buyers and sellers are mostly random, when they correspond to strategic decisions on the bilateral part of the market. Proximities play a central role on the decentralised market when they are not significant on the centralised one. A fixed-effect GLM model, where the network statistics are used as variables show that centrality influences the transactions prices in the same way, on the auction market and the bilateral ones. However, two other GLM estimations show that trust differently influences the prices and quantities exchanged, according to the market design.

This article is organised as follows : section 4.2 outlines the main characteristics of the market and presents the database. The statistical framework is presented in section 4.3. Section 4.5 presents the econometric models and the results. The conclusion follows.

4.2 The main market features and the data

We study here the functioning of the Boulogne s/mer fish market, through the analysis of a detailed database, consisting of 300000 daily transactions on the period 2006-2007.

The market : The Boulogne-sur-Mer fish market is located in the North of France near Belgium and considered as the most important fish market in France in terms of quantity. Its structure changed over time and for a long period, this market operated as a decentralised one. In the beginning of the 90*s* and following E.U. instructions, the market moved to an auction system, soon rejected by both buyers and sellers, alla arguing that the new market design was not in their favour. After collective bargaining between the different partners (institutions and unions of producers), a double mechanism has been introduced the 1st of April 2006, where both auction and bilateral sub-markets coexist.

This market is a daily one, open 6 days a week. Transactions begin early in the morning. Sellers are fishermen and buyers are restaurant owners, retail buyers and fish processors. Buyers form then an heterogeneous population, facing different budget and time constraints. They can freely buy on the two sub-markets. Each day, sellers have the possibility to choose how to sell their fish (centralised or decentralised mechanism). Once the sub-market chosen, sellers cannot change their strategy until the next day for practical reasons (costs of bring the merchandise from one part of the market to the other are very high). Mignot, Tedeschi & Vignes (2012) show the existence of two behaviours : some agents purchase most of the time on the same sub-market, when others switch regularly. Loyal sellers, the ones who change rarely, are mainly present on the bilateral market.

The auction market opens at 4 a.m. and always operates at the same place. During the studied period, the auction was an ascending one on 7 charts at the same time. It is a non cooperative game and the prices reflect the intensity of competition. Transactions on this sub-market are anonymous and the buyers are not supposed to interact with the auctioneer, apart from the prices formation mechanism. The time constraint is high, all transactions take place in 4 hours. Important volumes of fish are traded and transactions occur at a fast rate.

On the bilateral market, the prices are not displayed and emerge from a bargaining process. Buyers, who are retailers are looking for specific species, that correspond to their expected demand. Here agents have different source of private information, depending on their past history and their intensity to bargain and transact.

The data : 200 boats are registered in this market and are considered as sellers. 100 buyers purchase regularly, most of them on both sub-markets. The database we use covers a year and a half (2006-2007) where both sub-markets coexist. For each transaction, the date, the species, the characteristics of the traded fish (size, presentation, quality), buyer's and seller's identities, the type of trade mechanism (auction or negotiated), the quantity exchanged and the transaction price are known. In what follows, we focus on the post-reorganisation period, to evaluate the differences in the influence of trust on the outcomes of the two market designs. The analysis of the database tells a story of heterogeneity. First statistical results show that both buyers and sellers differ in terms of quality and quantities exchanged.

Moreover, the two submarkets (auctions and negotiated) have an equal importance : same agents transact on the two "submarkets" and the same types of fish are sold through both mechanisms (80 species of fish traded).

4.3 Stylised facts

After the introduction of the double mechanism, traders can decide to play randomly between the two submarkets or to favour one. Auctions do not allow loyal strategies unlike the decentralised market where people can choose with whom they exchange.

4.3.1 The fish market : A buyer perspective

Consider a bilateral market, where there is no arbitrage, composed by N buyers i, with $i = 1...N$ and M sellers s, with $s = 1...M$ who buy and sell regularly during τ periods, τ=1...T. At each period τ, a buyer (seller) can be present or not. When present, he can exchange with one or more sellers (buyers). In each bargaining bin, players trade with a partner they trust or with one randomly matched. The degree of buyers gives an idea on the number of connected sellers to each buyer. Because we believe that trust is higher on the negotiated submarket, we begin by analysing the degree from a buyer perspective.

A - The degree distribution

This section studied buyer's behaviour on each submarket. Do buyer behaves differently when choosing their sellers on both submarkets ? A study from the buyer side is presented assuming that the buyer is the one who decides in the first place. For each buyer, we denote :

- $\eta_i^{negotiated}$ as the degree of a buyer i on the negotiated submarket : the number of connected sellers from April 2006 till December 2007
- $\eta_i^{auction}$ as the degree of a buyer i on the auction submarket : the number of connected sellers from April 2006 till December 2007

Figure 4.1 and 4.2 pictured the degree distribution of buyers on both submarkets. At first glance, a difference for the degree distribution between both submarkets can be clearly seen. Therefore, a first deduction can be made : do buyers on the Boulogne-sur-Mer fish market behave differently among both designs ?
It is clear that the distribution on the negotiated market does not follow a normal distribution, unlike the auction market.

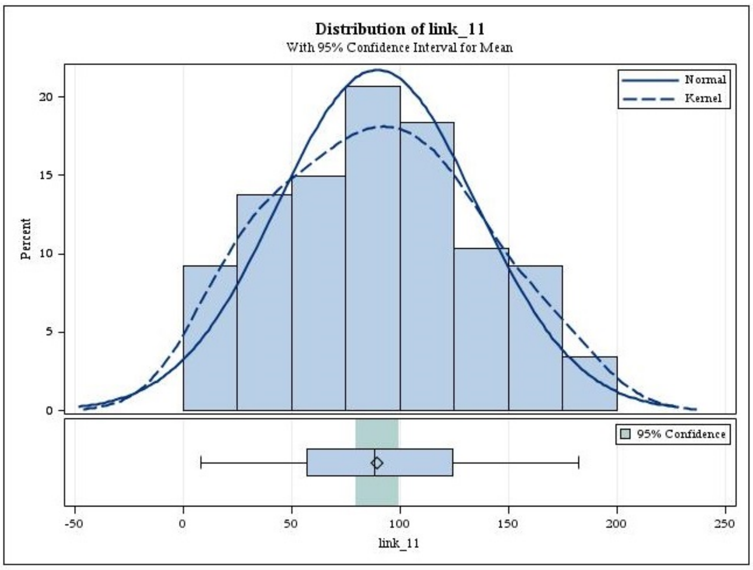


FIGURE 4.1 – The buyer degree distribution on the auction.

Test	Statistics	p Value
Anderson Darling	0.39	>0.25
Kolmogorov-Smirnov	0.0549	>0.1500

TABLE 4.1 – Normality test on the auction market

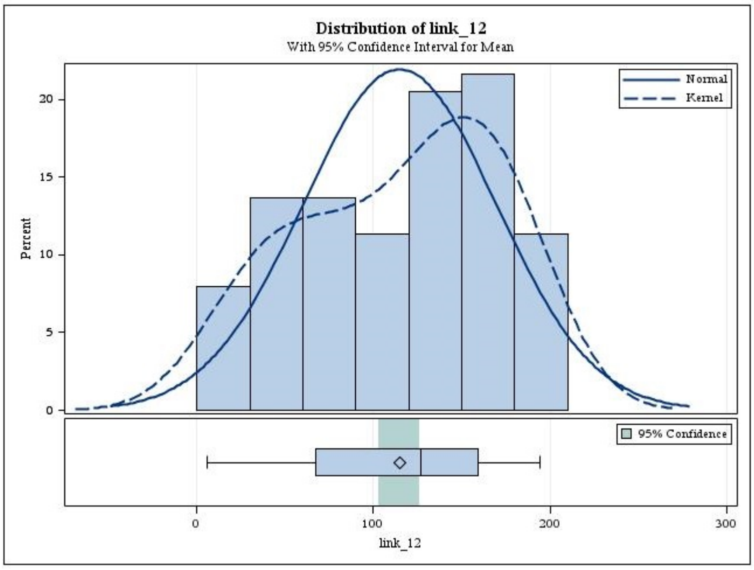


FIGURE 4.2 – The buyer degree distribution on the negotiated market.

Test	Statistics	p Value
Aderson darling	1.82	<0.005
Kolmogorov-Smirnov	0.116	<0.0100

TABLE 4.2 – Normality test on the negotiated market

Table 4.1 and 4.2 represent the Kolmogorov-Smirnov and the Aderson-Darling that test the null hypothesis for a sample. The results showed if this sample comes from a

normally distributed population or not. On the Boulogne-sur-Mer fish market, we may reject the null hypothesis on the negotiated submarket unlike the auction submarket using the Kolmogorov-Smirnov and the Aderson-Darling tests.
We do not reject the hypothesis that our variable follows the normal law on the auction submarket, unlike the negotiated one where it is obvious that our distribution does not follow the normal law. Hence, we reject that our variable follows the normal distribution on the negotiated one.

	Negotiated	Auction
Mean	112	84
Std deviation	53	41
Skewness	-0,3	-0,04
Kurtosis	-1,16	-0,9
Variance	2831	1699
Median	126	86
Mode	29	57

TABLE 4.3 – Degree descriptive statistics from the buyers side

As it can be observed in table 4.3, the median on the negotiated market is significantly higher than the mean, what reveals that this submarket (the negotiated one) has much smaller values than the auction submarket, and thus the probability to have less sellers on the negotiated market is more important.

The zero value of the skewness on the auction market shows that the degree distribution for the buyers on the auction market follows a normal distribution, and the kurtosis value on the negotiated market (-1,1) shows that the buyers degree distribution on this market follows a continuous uniform distribution [1].

1. These distributions represents for the buyers and the sellers who came to the Boulogne-surMer fish

We therefore verify the equality of means on both submarket using also the Satterthwaite and pooled method.

Equality of Variances		
Method	F Value	Pr>F
Folded F	1.61	.057

We use the t-test to determine whether the degree mean is different (significantly) among both designs. Satterthwaite test (tableau 4.4) proves this difference.

Methode	t value	Pr>|t |
Satterthwaite	-3.42	.0008
Pooled	-3.34	.0011

Table 4.4 – Difference of means test

To sum up, the degree analysis in a bipartite networks shows that buyers, when they are choosing their sellers, act differently.

B - The degree-presence distribution

To better understand this dissimilarity in buyers' manner, we consider the number of presence days for each of these buyers on each submarket. We want to see if this difference in the degree distribution is related to the number of presence on each designs. Therefore, we consider for each buyer i the following ratio : his degree over the number of presence day.

Figure B.5 shows the distribution of the number of days buyers purchase his fish on each submarket. The average exchanging days on the negotiated submarket [auction] for buyers is 258.64 [196.83] with a standard deviation of 173.34 [167.99].

market at least 10 times

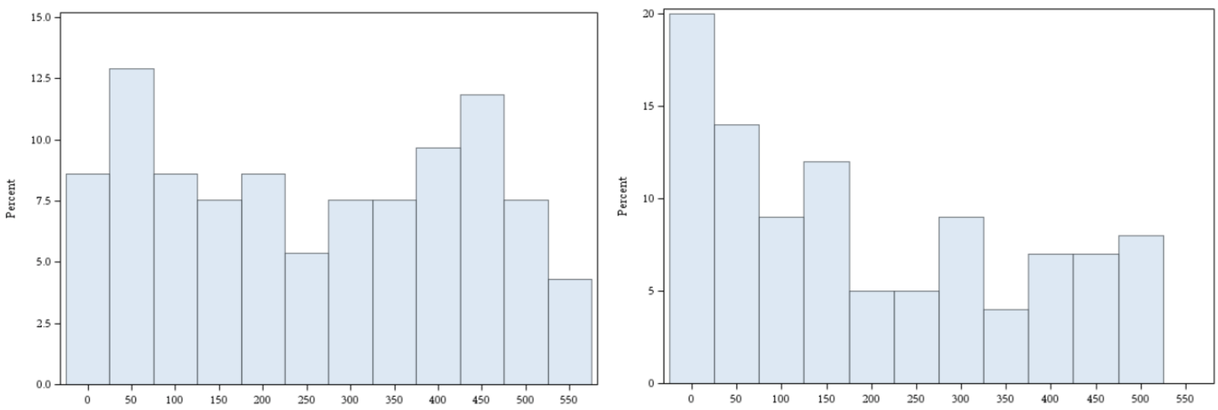


FIGURE 4.3 – Distribution of the number of presence day for N buyers on negotiated [left] and auction [right] submarkets.

Figure 4.4 pictures the distribution of this ratio (the degree over the presence days) on both submarkets. Agents behaviours is more homogeneous on the negotiated market than on the auction market (the skewness and the kurtosis are higher on the auction submarket).

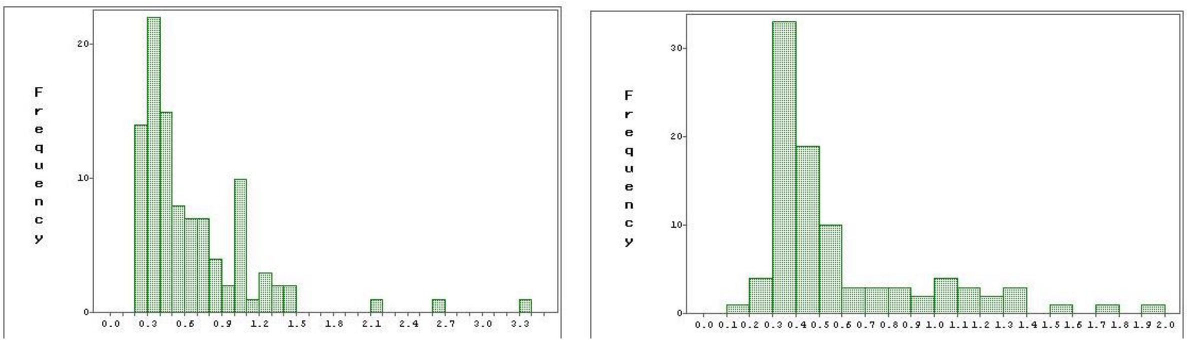


FIGURE 4.4 – The buyer degree-presence distribution on the auction (left) and the negotiated (right) submarkets.

	Negotiated	Auction
Mean	0.58	0.66
Std deviation	0.358	0.484
Skewness	1.710	2.778
Kurtosis	2.627	10.972
Variance	0.128	0.234
Median	0.419	0.489

TABLE 4.5 – Degree-presence descriptive statistics from the buyers side

Table 4.5 displays the descriptive statistics of the degree-presence ratio. The mean on the negotiated market is slightly lower than the mean on the auction market and so on for the skewness, the standard deviation and the kurtosis. A low ratio shows that a buyer had few links over an important presence day on the market. It means that this buyer trusts more people in his transaction. A buyer with a high ratio - defined by a high number of linked seller over a lower number of presence - shows that this buyer doesn't really have preferred seller (the ones he trusts) ; hence, he buys from everyone.

Quantile	Auction	Negotiated
100% Max	3.33	1.92
99%	2.96	1.92
95%	1.375	1.333
90%	1.188	1.16
75% Q3	0.85	0.68
50% Median	0.489	0.419
25% Q1	0.3375	0.3624
10%	0.2908	0.321
5%	0.279	0.288
1%	0.2409	0.1211
0% Min	0.2405	0.1211

TABLE 4.6 – Quantile on the auction and on the negotiated submarkets

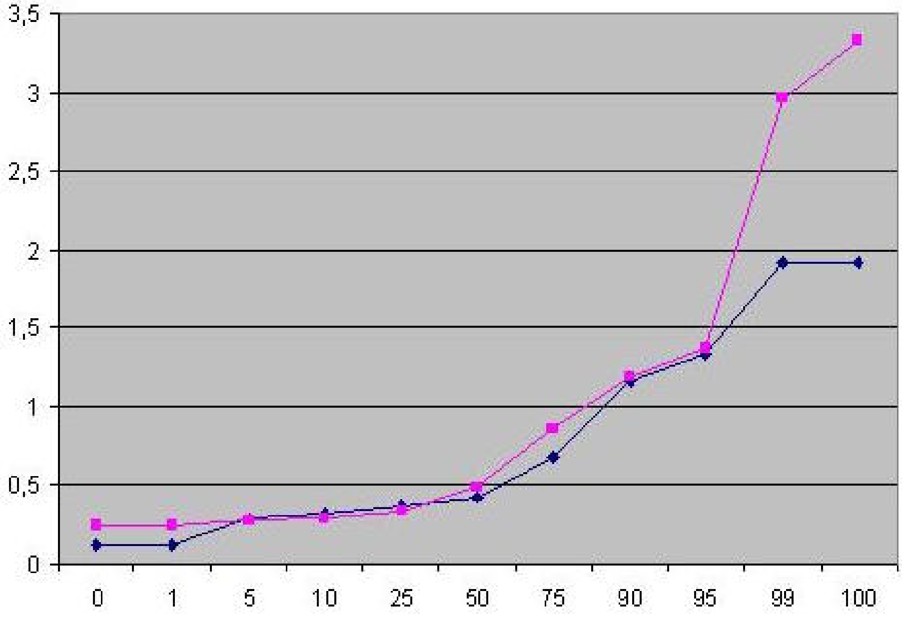


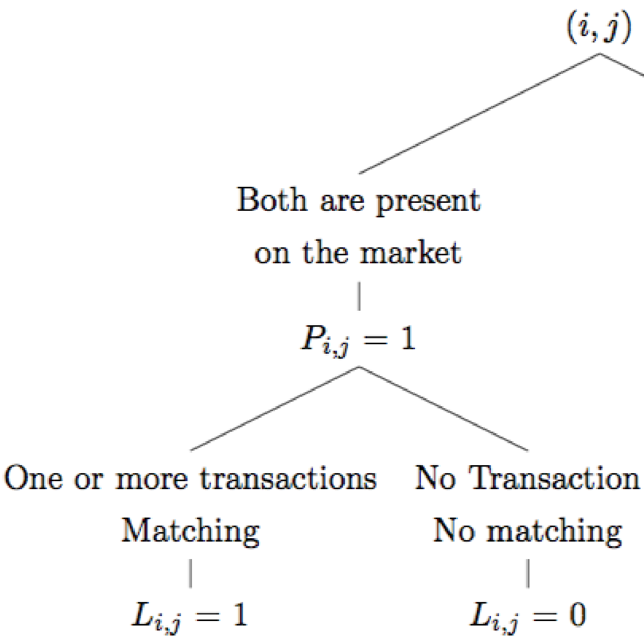
FIGURE 4.5 – The quantile on both submarkets

Figure 4.5 draws the quantile on both sub-markets. The bleu line represent the negotiated market and the pink one the auction one. We remark that the bleu line is always under the pink line, what proves that ratio on the negotiated market is lower. Considering the presence days and the number of connected sellers, buyers on the negotiated submarket behave in a distinct way. Can this be related to the intensity of links created between the buyers and the sellers on this fish market ? Section 4.3.2 introduces an attempt to measure this intensity of link between a couple (formed by a buyer and a seller).

4.3.2 Find a match and trust : A couple perspective

After admitting that buyers are not similar, in this section, a definition of finding a match and a trust ratio between the buyers and the sellers are done.

- The diagram below represents the different possibilities for each couple (seller, buyer) present at time τ on the market :



In the rest of the paper, we use the following notations :

- $m_{i,j}^T = \sum_{\tau=1}^{T} L_{i,j,\tau}$: Number of days a couple meets and transacts (we will refer to it as number of encounters) over all the period T
- $M_{i,j}^T = \sum_{\tau=1}^{T} P_{i,j,\tau}$: Number of days a couple is present on the market over all the period T
- $D_{i,\tau}$: Degree of buyer i at time τ (number of sellers linked to i at time τ)
- $n_{i,\tau}$: Number of buyers present on the market at time τ
- $n_{j,\tau}$: Number of sellers present on the market at time τ
- $D_{j,\tau}$: Degree of seller$j$ at time τ (number of sellers linked to i at time τ)

After introducing the terms composing the trust index, our trust is defined as a stock and strongly depends on the number of encounters between different people. The more a couple exchanges, the higher is their level of trust. The trust index below $R_{i,j}$ allows to associate a level of trust to each potential couple (i, j) of the market.

$$R_{i,j}^T = \frac{m_{i,j}^T}{M_{i,j}^T} - \frac{\sum_{\tau=1}^{T} [\frac{D_{j,\tau}}{n_{i,\tau}} + \frac{D_{i,\tau}}{n_{j,\tau}} - \frac{D_{j,\tau} * D_{i,\tau}}{n_{j,\tau} * n_{i,\tau}}]}{M_{i,j}^T} \tag{4.1}$$

This ratio can be explained by dividing it to two expressions. The first quotient explains the strategic decision for linking and the second one represents the random choice.

The first term $\frac{m_{i,j}^T}{M_{i,j}^T}$ shows the probability for a buyer i to transact with a chosen seller j. The second one $\frac{\sum_{\tau=1}^{T} [\frac{D_{j,\tau}}{n_{i,\tau}} + \frac{D_{i,\tau}}{n_{j,\tau}} - \frac{D_{j,\tau} * D_{i,\tau}}{n_{j,\tau} * n_{i,\tau}}]}{M_{i,j}^T}$ shows the probability for the buyer i to transact with the seller j if the seller j is chosen randomly. As Granovetter (1973) said, mutual confiding matters. Hence, the second term of equation 4.1 considers both agents degrees on a market where buyers and sellers can both choose between trusting behaviour or not.

Equation 4.1 proposed in this article is used to verify that agents behaviours are not similar on both submarkets. Its purpose is not only to illustrate the agents behaviour but also to pinpoint that trust level is not the same and agents are more strategic and make more choices on the negotiated market.

The trust index can take negative values as well as positive ones. A negative ratio shows that a buyer chooses in a random way his seller. He thinks less in choosing from whom to buy. The probability for a buyer i to choose randomly his seller j is more important that the probability of making choices. Whereas for a positive ratio, the probability for making choices is greater than the probability of choosing randomly. Thus, the buyer decides about his seller. He makes more choices, he distincts and prefers between the sellers on the market.

Figure 4.6 displays the distribution of the random vs trust ratio (equation 4.1) on the negotiated and on the auction market.

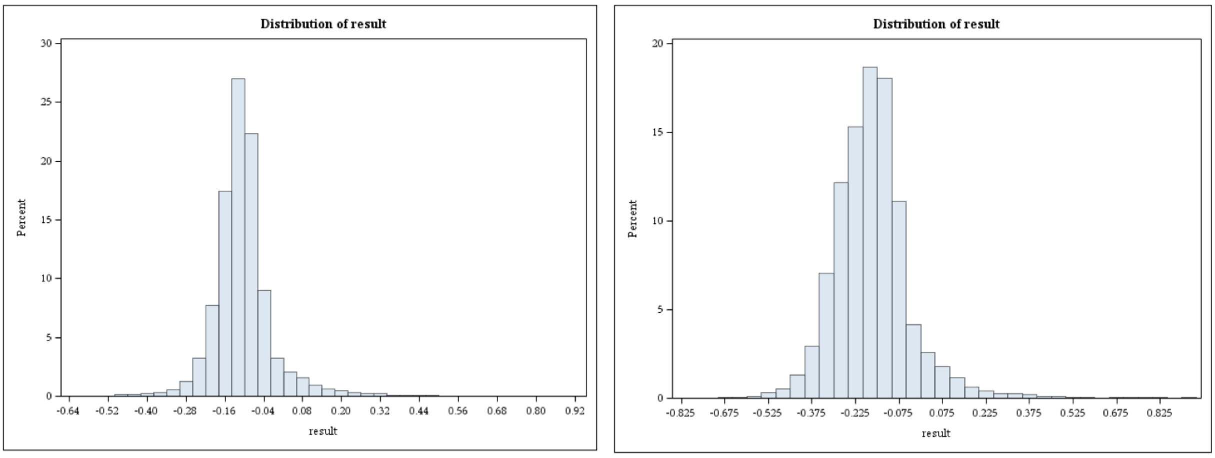


FIGURE 4.6 – The distribution of the trust ratio on the negotiated (left) and the auction (right) submarkets

Figure 4.6 shows the distribution of the random vs trust ratio on both submarkets : the negotiated and the auction submarkets (Table 4.7). We observe that on the auction submarket, the negative values are more important. Technically speaking, a negative value correspond to the fact that some people are matched randomly.

Looking at the random vs trust ratio (equation 4.1), we remark that on auction submarket, agents choose more randomly from whom to buy and they do not make much choices.

Oppositely, agents on negotiated submarket make more choice. Figure 4.6 highlights more negative ratios on the auction market and more positive ratios on the negotiated market (kurtosis and skewness values in table 4.7).

	auction	negotiated
Mean	-0.17	-0.10
Std Dev	0.14	0.10
Kurtosis	8.19	17.76
Skewness	1.5	2.48

TABLE 4.7 – Main statistics of the distribution of the trust vs random ratio on the negotiated and the auction market

As both variances on the auction and the negotiated markets are not the same (table 4.8), we test the equality of means on both submarket using the Satterthwaite method for unequal variances.

Satterthwaite test shows that the mean values for the trust versus random ratio on both submarkets are significantly different. The mean on the negotiated submarket is more important than on the auction submarket.

Equality of Variances		
Method	F Value	Pr>F
Folded F	1.82	<.0001

Methode	t value	Pr>|t |
Satterthwaite	-46.81	<.0001

TABLE 4.8 – Equality of variances and Satterthwaite test

4.4 Network analysis

4.4.1 Bipartite network

This section analyses, in a bipartite approach, the set of links between people as a social network (heterogenous individuals).

The purpose here is to compare the differences in terms of relations between buyers and sellers between both submarkets. To do so, we build for each submarket a bipartite network formed of two types of nodes, buyers and sellers, on the total period.

We describe a graph as a set of nodes where buyers (the grey nodes) and sellers (the back nodes) interact and we track the intensity of the relation among people [2].
We measure the link between two nodes using the trust index (equation 4.1) defined in the upper section.
We consider in what follows all the link that are created between agents when making choices (we do not consider the links created by random matching). Hence a link is formed between a buyer and a seller for a ratio higher than 0,1, otherwise there is no link. This threshold is chosen because it allows us to distinguish between a random matching (the set of these matchings describe a quasi-complete network) and a strategic one.

$$Link_{i,j} = \begin{cases} 1 & \text{if } R_{j,i} \geq 0.1 \\ 0 & \text{else} \end{cases} \tag{4.2}$$

At first sight, both graphs in figure 4.7 are not similar. On the negotiated submarket, some buyers have a set of "preferred" sellers, unlike the auction submarket where all the sellers and buyers are centralised.

2. the grey nodes are represented by green nodes, and the back nodes by red color

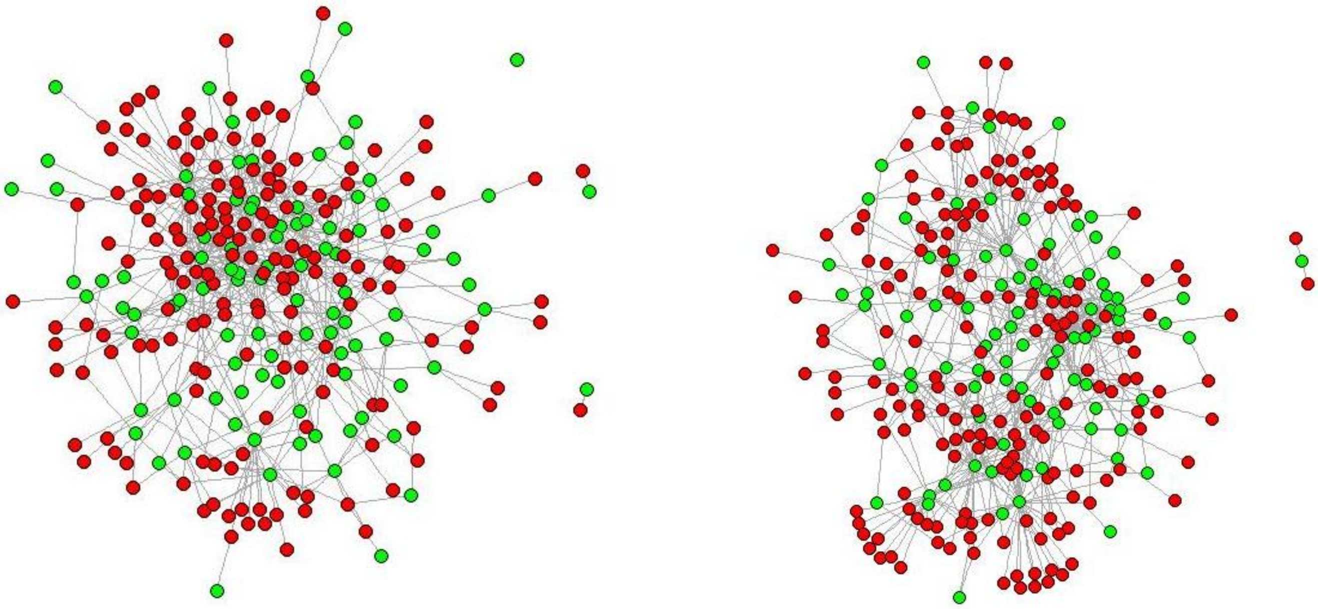


FIGURE 4.7 – A bipartite graph for auction (right) and negotiated (left) submarkets : sellers are in black, buyers in grey

	auction	negotiated
Nodes	272	278
Links	592	629
Density	0.016	0.015
Assortativity	-0.023	0.0165

TABLE 4.9 – Networks statistics

The density of a network is the fraction between the number of created links and the number of total possible links. The density value is between 0 and 1. A density close to 1 reflects a very dense network with an important number of links and when it is closed to 0, the network has very few links. Both submarkets have a similar density equal to 0.015. Do high degree nodes tend to connect with other high degree nodes, or do they prefer to establish a link with low degree ones ? A different measure used in the literature is the assortativity. Therefore, this coefficient explains the capacity of a node to create a link with a node that is similar. It measures the correlation between two nodes giving a value between -1 and +1. Our assortativity ratio is not the same for both submarkets. It is negative for the auction market (-0.023) and that could be explained by important buyers who transact with many small sellers or important sellers (rational ones) who sell to many small buyers what explain figure 4.7. The assortativity ratio is positive on the negotiated submarket that could suggest that links are based on something other than pure economics relationships ; and that could be clarified by important buyers who transact with many important sellers (rational ones) or small sellers who sell to many small buyers.

4.4.2 Projected network

To better estimate the role of centrality, we project now the bipartite network on homogenous one.
A buyer is linked to another buyer if both of them transact with at least the same seller (one or more). As well, sellers are linked if they transact with at least the same buyer (one or more).

Figure 4.8 and 4.9 picture buyers and sellers projected network.

Buyers projected network

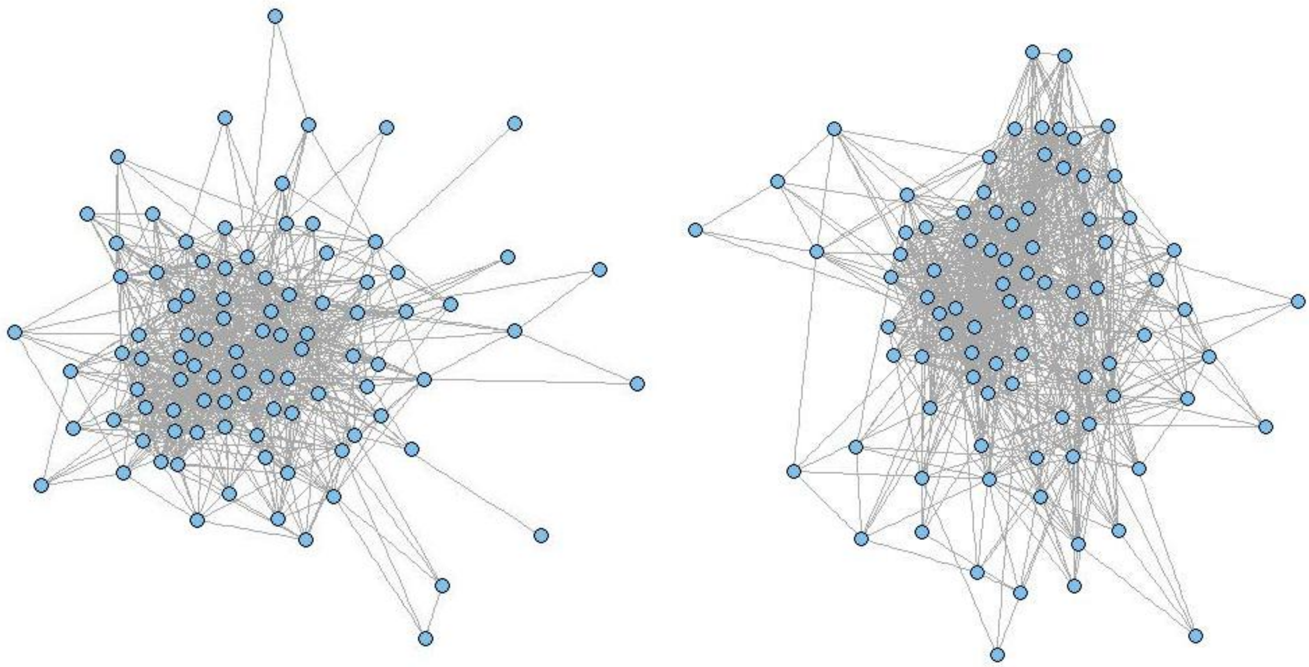


Figure 4.8 – Buyers projected network (auction (left) negotiated (right))

	auction	negotiated
Nodes	95	88
Links	866	998
Density	0.1939	0.2607
Assortativity	0.205	0.0501

Table 4.10 – Buyers projected graph statistics

Even thought their is no remarkable difference between both submarkets for numbers of nodes, a difference can be noted for the number of links as for the density. Buyers on the negotiated submarket are more linked, hence they have more common sellers. One interpretation is that buyers visit more sellers on the decentralised market. The assortativity is lightly higher on the auction market. To explain the higher density on the negotiated market, we calculate for each buyer and seller how many days they take to return to the market. In other words, we determine for each buyer and seller the time period between two presence on each submarket. In average a buyer returns to the auction market each 19 days and each 5 days to the negotiated one. As for the seller, they sell in average each 14 days on the auction market and each 6 days on the negotiated one (Table 4.11) .

	Buyer		Seller	
	Auction	Negotiated	Auction	Negotiated
Mean	13.78	6.26	18.59	4.87
Std Dev	34.08	15.59	17.19	3.67
Kurtosis	17.53	40.29	6.12	20.97
Skewness	4.08	5.90	2.01	3.91

TABLE 4.11 – Descriptive statistics buyer and seller sides

Sellers projected network

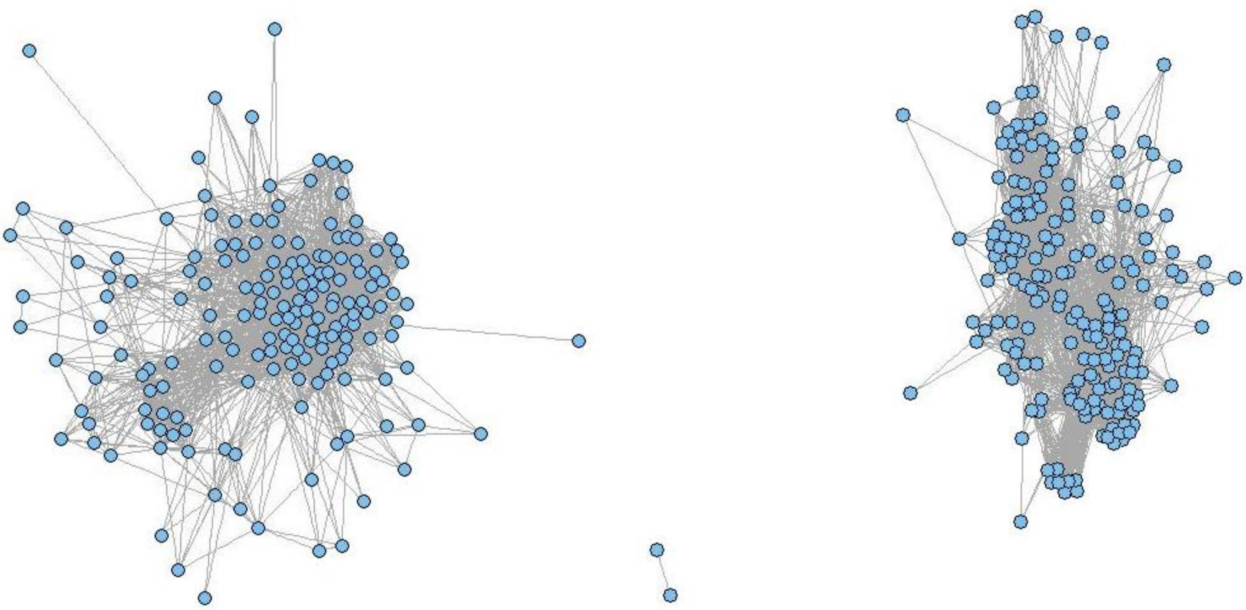


FIGURE 4.9 – Sellers projected network (auction (left) negotiated (right))

Sellers projected graph shows the number of links created on auction and negotiated submarkets is the same which explains the same density. The assortativity on the auction market is twice the one on the negotiated market (see table 4.12) and on both submarkets they are positive.

This is in line with the assortativity level on the bipartite network (table 4.9) for the negotiated submarket ; the positive assortativity close to zero suggests that links are based on something other than pure economics relationships. Linked sellers have similar characteristics and therefore are connected to similar buyers.

	auction	negotiated
Nodes	173	189
Links	2710	3321
Density	0.1821	0.1869
Assortativity	0.1	0.04

TABLE 4.12 – Sellers projected graph statistics

4.5 The Econometric Models

We now explore how the trust propensity and the individual position in the social network influences the outcome of the market. A first model evaluates the influence of Bonacich (1987) centrality and betweenness on transactions prices. Models two, three and four evaluates the influence of the trust ratio as defined section 4.3 on the quantities and prices exchanged by pairs of buyers and sellers. In this section, we will see if our ratio affects in a different way the prices and the quantity on both submarkets, and the influence of centrality on prices.

4.5.1 Model 1 : Centrality analysis

We begin by analysing the effects of centralities on prices. The objective is to see whether the position of the agents in the networks influences the prices they will pay (or get). Because of seasonality (see Mignot et al. (2012)), we know that the price of a transaction also depends on the day of the week ($Weekday_k$). We control for the global significance of the 80 species ($Species_k$) exchanged. The explained variable is the price of a transaction k . Each transaction k involves a buyer, a seller and a species. We also control for the identity of the seller ($boat_k$) and the buyer ($buyer_k$). The centrality used are the Bonacich centrality (bon_k) and the betweenness centrality (bet_k)

$$P_k = \beta_1+\beta_2 \cdot Bon_k+\beta_3 \cdot Bet_k+\beta_4 \cdot Species_k+\beta_5 \cdot Weekday_k+\beta_6 \cdot boat_k+\beta_7 \cdot buyer_k+\beta_8 \cdot mois_k+v_{i,t} \tag{4.3}$$

$$v_{it} = \mu_i + \delta_{it}, \quad \mu_i \sim i.i.d.(0, \sigma^2_{\mu_i}), \quad \delta_{it} \sim i.i.d.(0, \sigma^2_\delta) \tag{4.4}$$

The results

We use this model with the centrality coefficient of the four homogenous graphs 4.8 and 4.9. At first glance, the results are quite paradoxical. Concerning the sellers homogenous network (the one where two sellers are linked when they share one or more buyers), the different centralities do not have the same influence on prices. The more central a seller is (the more buyers he shares with competitors), the lower the prices are (See table 4.13). If these results correspond to some economic evidence, they remain paradoxical in the fact that they are not identical on both submarkets. There are no significant effect on price when auctioning. The place where people are affects their outcomes. Concerning the buyers homogenous network (where buyers are linked when they share at least one seller), there is non significant effect of their position on the negotiated submarket. A significant negative influence is therefore on the auction one (See table 4.14). This suggests that, buyers on the auction submarket are more strategic, they buy from everyone in order to get lower prices. This category can be explained by the big buyers who buy important quantities at lower prices. This is not the case on the negotiated submarket. Buyers do not intend to negotiated in order to get lower price. The importance of the network is not therefore linked to price. Personal relationships, which are strong enough to design the network, play an other role than a pure economic one.

	Auction			Negotiated		
Parameter	coefficients	Std err	$Pr > \|t\|$	coefficient	Std err	$Pr > \|t\|$
Intercept	1.36	1779	0.999	1.14	2338	0.999
Bonacich	-0.56	1196	0.999	-0.24	0.098	0.013
Betweeness	-0.20	496	0.999	0.058	0.021	0.007

TABLE 4.13 – Sellers on auction and bilateral submarkets

	Auction			Negotiated		
Parameter	coefficients	Std err	$Pr > \|t\|$	coefficient	Std err	$Pr > \|t\|$
Intercept	-1.02	0.298	0.0006	2.13	1032	0.999
Bonacich	-0.29	0.057	<.0001	0.44	183	0.999
Betweeness	0.197	0.045	<.0001	0.077	141.42	0.999

TABLE 4.14 – Buyers on auction and bilateral submarkets

4.5.2 Model 2 : Influence of trust index on prices

$$P_{i,j,t} = \beta_1 + \beta_2 \cdot R_{i,j} + \beta_3 \cdot i + \beta_4 \cdot j + \beta_5 \cdot Weekday_t + \beta_6 \cdot year_t + \beta_7 \cdot mois_t + v_{i,j,t} \quad (4.5)$$

	Negotiated			Auction		
Price	Coef	Std Dev	Pr > t	Coef	Std Dev	Pr > t
Intercept	4.94	0.43	<.0001	2.80	0.52	<.0001
$R_{i,j}$	0.22	0.034	<.0001	0.075	0.045	0.09

TABLE 4.15 – Estimation results for the negotiated and auction submarkets

This section seeks to explain how the trust index (equation 4.1) influences prices on auction and negotiated submarkets throughout time. To do so, we estimate the price transactions in a GLM model. We control the global significant of the weekdays, the years, the months, the buyers and the sellers. The explained variable is the price per couple and day.

The results are given in table 4.15. As it can be observed, significant coefficient are on the negotiated submarket and not on the auction one. We verify a positive relation between the prices and the trust index on the negotiated submarket. When people trusts each other, they get higher prices with time when negotiating. Hence trust increases price on the negotiated submarket and has no effect on the auction one. When auctioning, and as already proved in the previous chapters, trust can prevail because it is linked to the "boat's name". However no significant relation is noted : prices will not reflect this relation. One explanation can be given : because the sellers are not present and have no direct power when it comes to create intense bonds, the trust index, that reflects trust creation from both sides (a buyer and a seller), do not influence prices on the auction submarket.

Price R_{ij}	Coef	Std deviation	Pr>t
Cat1	0.172	0.11	0.1378
Cat2	0.204	0.1016	0.0442
Cat3	0.037	0.0177	0.0346

TABLE 4.16 – Estimation result on the negotiated submarket by fish categories

Table 4.16 gives the results for regression 4.5 for three different categories of fish. The three categories represents the type of the fish, from the most cheaper ones (category 1) to the most expensive ones (category 3). As we can see, our trust index plays an important role on the category 3 of the fish. This is not the case for the cheapest kind of fish where there are no significant relation between the trust index and the price.

4.5.3 Model 3 : Influence of the number of encounters on quantity

To explain if the numbers of encounters influences quantity, we compute the relation between the quantities exchanged $Q_{i,j}$ and the number of encounters between a buyer and a seller $m_{i,j}$ on the auction and the negotiated submarkets.

An econometric model is used to evaluate if trust affects differently the outcomes of the transactions for both submarkets. In this model we use :

- The quantity exchanged between each couple : $Q_{j,i}$
- The number of encounters between (j, i) on both submarkets : $m_{j,i}$

We estimate the following equation :

$$Q_{j,i} = \beta_1 + \beta_2 m_{j,i} + +\beta_3 m_{j,i}^2 + u_{j,i} \tag{4.6}$$

where $Q_{j,i}$=$\sum_{t=1}^{T} q_{(j,i),t}$

for (j, i)=1,...,C (where C is the number of all the created couples). We explore here the influence of the different components of trust ratio on the quantity.

	Negotiated			Auction		
Log quantity	Coef	Standard Error	Pr>|t|	Coef	Standard Error	Pr>|t|
Intercept	3.502	0.0022	0.000	3.66	0.022	0.000
Log encounters	1.35	0.025	0.000	1.33	0.027	0.000
Log^2 Encounters	-0.013	0.006	0.02	-0.000	0.006	0.9104

TABLE 4.17 – Estimation results for the negotiated and auction submarkets

We remark that, on the auction and the negotiated submarket, the quantity exchanged increases with the number of encounters. It grows with an increasing rate at the auction market and a decreasing one on the negotiated market. So when a couple meet more frequently, it is obvious that they exchange more quantity on the auction market, when it is not truly the case on the negotiated market. The results of the estimation are given in table 4.17. We observe significant coefficients for all the explaining variables. We verify a negative relation between the quantity and the $encounters^2$ on the negotiated submarket and a positive one on the auction submarket. This decreasing rate demonstrates the fact that when trust is created and buyer gets to know his seller, he consequently moves to a different quality of fish. As previously mentioned trust plays an important role for expensive fish and for that reason the decreasing rate prove the switching to better quality and to higher price on the negotiated submarket.

To better understand trust results, we analyse in what follows, how the prices are affected by our ratio.

4.5.4 Model 4 : Influence of the number of encounters on price

This model explains the relation between the price and the trust ratio. where

$$P_{j,i} = \frac{\sum p_{j,i} * q_{j,i}}{\sum q_{j,i}} \tag{4.7}$$

is the price index for the different species exchanged.

$$P_{j,i} = \alpha_1 + \alpha_2 m_{j,i} + \alpha_3 m_{j,i}^2 + u_{j,i} \tag{4.8}$$

	Negotiated			Auction		
Log Price	Coef	Standard Error	Pr>|t|	Coef	Standard Error	Pr>|t|
Intercept	1.059	0.015	0.000	1.118	0.016	0.000
Log Encounters	0.227	0.017	0.000	0.11	0.019	0.000
Log $Encounters^2$	-0.037	0.004	0.000	-0.217	0.005	0.000

TABLE 4.18 – Estimation results for the negotiated and the auction submarkets

As we can see, there is no significant difference between both submarket at a price level. When agents meet more, prices get higher. Buying continuously from the same seller increases prices on both designs. Model 4 reflects the importance of the "boat-name" and reputation on centralised market where the sellers are powerless. Buyers will compete in order to get the goods what explain the positive coefficient in the regression.

4.5.5 Model 5 : Influence of the number of encounters on price and quantity for the different categories

In order to understand why a difference exists at a quantity level and not at a price level, we estimate both regressions for the different categories of the species. We differentiate three categories : the first one, "category auction" includes the species that are more expensive on auction submarket, while category two, "category negotiated" is composed of fish that are more expensive on negotiated submarket and the third category "category neutral" combines fish that have no significant difference in terms of prices between both submarkets.

Log quantity	Negotiated			Auction		
Category Auction	**Coef**	**Std Dev**	**Pr > |t|**	**Coef**	**Std dev**	**Pr > |t|**
Intercept	3.217	0.025	<.0001	3.36	0.026	<.0001
Log Encounters	1.414	0.034	<.0001	1.304	0.035	<.0001
Log^2 encounters	**-0.012**	**0.009**	**0.1905**	0.0244	0.009	0.0068
Category Negotiated	**Coef**	**Std Dev**	**Pr > |t|**	**Coef**	**Std dev**	**Pr > |t|**
Intercept	3.01	0.173	<.0001	3.10	0.02	<.0001
Log Encounters	1.313	0.024	<.0001	1.244	0.034	<.0001
Log^2 encounters	-0.23	0.006	0.0003	**-0.01**	**0.011**	**0.3643**
Category Neutral	**Coef**	**Std Dev**	**Pr > |t|**	**Coef**	**Std dev**	**Pr > |t|**
Intercept	3.41	0.026	<.0001	3.67	0.027	<.0001
Log encounters	1.44	0.036	<.0001	1.39	0.037	<.0001
Log^2 encounters	**-0.016**	**0.001**	**0.0996**	-0.022	0.009	0.0198

TABLE 4.19 – Estimation results for the negotiated and the auction submarkets

Log Price	Negotiated			Auction		
Category Auction	**Coef**	**Std Dev**	**Pr > |t|**	**Coef**	**Std dev**	**Pr > |t|**
Intercept	0.925	0.016	<.0001	0.864	0.018	<.0001
Log Encounters	0.194	0.022	<.0001	0.222	0.024	<.0001
Log^2 encounters	-.049	0.006	<.0001	-0.434	0.006	<.0001
Category Negotiated	**Coef**	**Std Dev**	**Pr > |t|**	**Coef**	**Std dev**	**Pr > |t|**
Intercept	1.374	0.016	<.0001	1.432	0.0176	<.0001
Log Encounters	0.127	0.022	<.0001	0.0835	0.03	0.0058
Log^2 encounters	**0.016**	**0.0058**	**0.7775**	-0.05	0.01	<.0001
Category Neutral	**Coef**	**Std Dev**	**Pr > |t|**	**Coef**	**Std dev**	**Pr > |t|**
Intercept	0.752	0.017	<.0001	0.766	0.019	<.0001
Log encounters	0.298	0.023	<.0001	0.187	0.026	<.0001
Log^2 encounters	-.057	0.006	<.0001	-.016	0.007	0.0198

TABLE 4.20 – Estimation results for the negotiated and the auction submarkets

Tables 4.19 and 4.20 give the results for price and quantity regression for the three categories of fishes for both submarkets. The difference that should be noted between the submarkets, is marked in bold. What we observe is that for all the categories for both submarkets, prices increase at an decreasing rate with the number of encounters. But only one category should be noticed : the species that are more expensive and sold on the negotiated submarket increase but not with the same rate as all the other categories (there is no significant relation between Log^2 encounters and the price).
As for the quantity, it increases at a decreasing rate for all the categories for both submarkets, but it increases at a increasing rate for the species that are more expensive and sold on the auction submarket. We note no significant relation between the Log^2 encounters and the quantity for the species that are more expensive on auction submarket but sold on the negotiated one, for the species that are more expensive on the negotiated submarket but sold on the auction one and finally for the species that have no difference in terms of prices between submarkets but sold on the negotiated one.

4.6 Conclusion

This article shows how on a particular market where the level of uncertainty is quite high and where people meet regularly, trust can affect the way the transactions are accomplished. Even with a very simple measure of trust propensity, we obtain quite interesting results. In all our empirical work, we refer to the level of trust between two persons by the number of encounters (number of day two persons traded together), relative to the number of days these two persons were present on the market. When two people exchange more together, they significantly reach higher levels of trust.

We bring into the light the fact that links between people depend on something else than pure economic determinants. Network statistics on a bipartite graph, show that assortativity on auction market clearly depends on some economic strategies (highly connected buyers trade with poorly connected sellers).When we project the bipartite network on two

different homogenous networks (a buyer one and a seller one), we observe that the density on the negotiated market is higher than on the auction one. This is due to the fact that people are more present on the negotiated market than on the auction one. Driving an econometric analysis, we observe quite paradoxical results. Concerning the sellers homogenous network (the one where two sellers are linked when they share one or more buyers), the different centralities influence negatively and significantly prices. The more central a seller is (the more buyers he shares with competitors), the lower the prices are. If these results correspond to some economic evidence, they remain paradoxical in the fact that they are identical on both markets. Despite different information structures, the place where people are affects their outcomes. Concerning the buyers homogenous network (where buyers are linked when they share at least one seller), there is non significant effect of their position neither on the auction market nor on the bilateral one. This suggests that personal relationships, which are strong enough to design two different networks (corresponding to the two different submarkets) play an other role than a pure economic one.
Looking at the influence of encounters on the quantities exchanged by pairs of agents (buyer/ seller), a GL model shows that this effect is different between the two markets. When we observe a concave effect on the negotiated market, we see an increasing effect on the auction market. It seems that encounters on the negotiated market have not the same consequences than on the auction market. Concerning the prices, we find a no significant differences between the submarket. But for the rust versus random ratio, we remark that it had no significant effect on price on the auction submarket, but a positive effect on the negotiated submarket. Can we relate this difference to the quality of fishes exchanged or to overconfidence on the negotiated submarket. This work is a very preliminary one but let the door open to more sophisticated estimations on the role of trust and the understanding of the emergence of trustworthy relationships.

Conclusion

"Markets and networks : the influence of interpersonal links on trade's efficiency".

This thesis addressed three major axes : market structure, network creation and interpersonal relationship of trust. The most important point was to highlight the link between the market structure, its effect on interpersonal relationships and thus the creation of networks. This thesis is a continuation of an existing literature on the comparison of the two market structures : the auction market and the negotiated market. It was targeted at this debate, and notably at highlighting the difference between market structures taking into consideration the links between buyers and sellers on a daily market of perishable goods : the Boulogne-sur-Mer fish market.

Three articles were used as a proof to show the different intensities of trust links existing among submarkets. Until now, no common definition of trust can be found, notwithstanding the numerous attempts philosophers and economists have made in order to characterise the trust and to measure it.

The first article of this thesis was based on a methodology used by ecologists. This methodology made it possible to measure the robustness and the nestedness of a network. The first results were quite interesting since they showed a difference between the bidding and the negotiation when it comes to the robustness of the network. After presenting the market Boulogne-sur-Mer fish market a adjacency matrix of interactions between buyers and sellers, we tried to detect the effect of the removal of an agent on the network. Different results were noted among the two structures ; the negotiated market turned out to be more organised than the auction. To understand this difference, an estimation of a fidelity index between buyers and sellers was made. This estimation indicated that the negotiated market performs a higher level of fidelity than the auction market.

After validating the robustness, the nested index and the higher level of fidelity on the negotiated submarket, the second article focused on trust from the buyer side. Moving from a searching state to the circle of trust, this article was based on the duration model to calculate the time of transition. Buyer will therefore find his match, his favorite seller. As a matter of fact, a parametric and a non-parametric models validated this difference of bonds between the two structures. Buyers were divided into three categories based on their preferences and duration model was tested and had shown different survival and hazard curves. More interesting results were associated to the size of the buyer. Small buyers, who prefer negotiated, are the most affected by trust, unlike the biggest buyers who prefer auction and have zero trust (horizontal survival curve). Finally, buyers, indifferent towards the two mechanisms, come in all sizes. Once on the negotiated market, most of them find their match.

Since trust is vital on the negotiated submarket, the latest model of this thesis focused on the effect of these inter-individual links on the terms of trade. A trust index, analysed in details, was created using a probabilistic method. Bipartite and projected graphs (homogeneous) of buyers and sellers were drawn. Dissimilarity was proven on the basis of the network analysis tools. Subsequently, four econometric models were tested. The first model, "analysis of centrality", tested the influence of the betweenness and Bonacich on prices. Whereas, model 2 studied the effects of the trust index on price. As for model 3, it was about the influence of numbers of encounters on prices and quantities. Finally, model 4 is a detailed version of model 3 taking into account the different types of fish in the market : fish sold at a higher price on auction, fish sold at a higher price on the negotiated submarket and finally fish having no significant difference in terms of price between the two designs.

To sum up, this thesis created a link between the market structure and the loyalty bonds between buyers and sellers and it proved that agents behave differently depending on the market structures and that loyalty is crucial on the negotiated submarket.

The Boulogne-sur-Mer database showed to be relevant for my approach and for upcoming ones such as comparing the data given from April 2006 until December 2007 with the data given before April 2006 (the date of the coexistence of the two structures). This study will show whether the agents have changed their behaviour on the auction market after the introduction of the negotiated market.

It will also be interesting to analyse the loss of trust, the influence of the loss of trust on prices and quantities using econometric models. Moreover, a new database would be interesting for the period beyond December 2007. This period will allow a detailed follow up on the behaviour of the agents.

"Marché et réseau : l'influence des liens interindividuels sur l'efficacité des échanges". Tout au long de cette thèse trois grands axes ont été étudiés : structure du marché, création du réseau et liens interindividuels de confiance. Le point le plus important était de mettre en avant le lien existant entre la structure du marché, son effet sur les liens interindividuels et donc sur la formation des réseaux. Cette thèse s'inscrit dans une continuité d'une littérature déjà existante et qui porte sur la comparaison des deux structures du marché : le marché des enchères et le marché de gré à gré. L'objet de cette thèse était non seulement de faire part de cette littérature mais plus spécifiquement de mettre en évidence cette différence de structures tout en prenant compte des liens de confiance construits entre acheteurs et vendeurs sur un marché quotidien de biens périssables : le marché de Boulogne-sur-Mer.

Philosophes et économistes ont essayé de caractériser et de mesurer la confiance, mais une définition unique n'a toujours pas été adoptée. Sa mesure restant en soi-même une ambiguité, ces trois articles demeurent une représentation d'une tentative de définition, de mesure et de comparaison de cette confiance entre deux mécanismes de vente. Ces articles susmentionnés sont des preuves qui démontrent la différence des intensités des liens de confiance crées entre acheteurs et vendeurs sur le marché de Boulogne-sur-Mer.

Le premier article de cette thèse s'est basé sur une méthodologie utilisée par les écologistes. Cette méthodologie définit la notion de "nested" et mesure la robustesse du réseau. Les premiers résultats obtenus ont été assez intéressants dans la mesure où ils ont démontré une différence entre les enchères et la négociation au niveau de la construction et de la robustesse du réseau. Après avoir présenté le marché de Boulogne-sur-Mer sous une forme d'une matrice adjacente de contactes entre les acheteurs et les vendeurs, nous avons essayé de voir si la suppression d'un agent affecterait notre réseau. De différents résultats ont été notés entre les deux structures ; le marché négocié est plus organisé que le marché des enchères. Afin de bien comprendre cette différence, une estimation de la fidélité entre acheteur et vendeur a été faite. Cette estimation avait prouvé que le marché négocié est marqué par une fidélité plus importante que le marché des enchères.

Après avoir validé une différence de robustesse, d'organisation et de niveau de fidélité entre les deux structures, le deuxième article de cette thèse a abordé les liens de fidélité du côté acheteur. Passant d'un état de recherche au cercle de confiance, ce dernier article s'est basé sur le modèle de durée pour calculer le temps mis par un acheteur pour trouver son match : son vendeur préféré. En effet, un modèle paramétrique et un modèle non-paramétrique ont validé cette différence deux structures. Les acheteurs ont été divisés en trois catégories selon leur préférence aux mécanismes de vente. Le modèle de durée a été testé pour ces trois catégories ; différentes courbes de survie et de hasard ainsi que des résultats intéressants liés à la taille de l'acheteur ont été constatés. Les petits acheteurs, préférant le gré à gré, sont les plus atteints par la confiance. Les acheteurs plus grands de taille et préférant les enchères ont zéro confiance (droite de survie horizontale). Finalement, les acheteurs indifférents des deux mécanismes, regroupent les acheteurs de toutes tailles. Une fois sur le négocié, certains acheteurs indifférents sont atteints par la fidélité.

La fidélité étant plus importante sur le marché de gré à gré, le dernier modèle s'est intéressé principalement sur l'effet de ces liens interindividuels sur les termes des échanges. Un indice de confiance, analysé en détail, a été crée en utilisant une méthode probabiliste. Les outils d'analyse des réseaux ont permis la construction des réseaux bipartites et des réseaux projetés (réseaux homogènes) des acheteurs et des vendeurs. Ces graphs ont appuyé la difference d'intensité des liens entre les deux structures. Par la suite, 4 modèles économétriques ont été testé pour voir l'effet de cet indice de confiance. Le premier modèle intitulé "analyse de centralité" a testé l'effet de betweeness et de Bonacich sur les prix alors que le modèle 2 a étudié les effets de l'indice de confiance sur les prix. Quant au modèle 3, il a étudié l'influence du nombre de rencontres sur les prix et sur les quantités. Et finalement le modèle 4, a détaillé dans son contenu le modèle 3 tout en exploitant les différents types de poissons. Une catégorisation des poissons a été prise en compte : poisson vendu plus cher sur le négocié, poissons vendus plus cher sur les enchères et poissons qui ne présentent pas de différence significative de prix entre les deux marchés.

Somme toute, cette thèse a prouvé une relation entre la structure du marché et la construction des liens de fidélité entre acheteurs et vendeurs. Tout en tenant compte des liens interpersonnels, le comportement des agents est différent entre les structures.

La base de donnée de Boulogne-sur-Mer utilisée est très intéressante. De nombreuses extensions de cette thèse sont possible telle une comparaison avant le mois d'Avril 2006, la date de la coexistence des deux structures. Cette étude permettrai de voir si les agents et plus notamment les acheteurs, ont changé de comportement sur le marché des enchères suite à l'introduction du marché négocié.

Il serait encore intéressant d'analyser la perte de confiance. Des modèles économétriques permettront de voir l'effet de cette perte sur les prix et les quantités. Finalement, une base de donnée portant sur la période au delà de Décembre 2007 pourrait être intéressante. Cette période permettra de suivre d'une façon plus détaillée les comportement des agents jusqu'à présent.

Table des figures

Liste des tableaux

Appendices

A Data and Descriptives

A.1 A day on the Boulogne-sur-Mer fish market

How the coexistence of the auction and the negotiated submarket took place ?

The Boulogne-sur-Mer fish market operated under different structures. First, it worked under the negotiated mechanism. But year after year, the quantity of fish was decreasing due to overfishing, pollution and climate change. In the 80's, quotas were then introduced to protect stocks and producers, what reduced production capacity. Because this quota was new in the world of fisherman, the U.E. organisers suggested to help the agents on the Boulogne-sur-Mer fish market. They convinced them that in order to be more efficient and to not waste fish, the auction structure is the solution. Therefore everyone will get the right price and no one will lose. The auction submarket was then constructed on the Boulogne-sur-Mer. From the year 2000 until 2005, all the fish on the Boulogne-sur-Mer market were only auctioned. But agents protested against this organisation [1], and it was suggested to add the negotiated submarket in April 2006.
Nowadays, the Boulogne-sur-Mer fish market is characterised by the stable coexistence of these two selling mechanisms : the auction and the negotiated.

So how this market works ? It can be resumed as follows and the details are given af-

1. the sellers protested that prices are low and buyers protested that prices are too high ! !

terwards. Daily, sellers and buyers choose their submarket. They have the choice between both designs : auction and negotiated. The auction and the negotiation took place at the same place and the same time. Sellers cannot switch between submarkets, but buyers can. In average, the 208 sellers came 152 days on the Boulogne-sur-Mer fish market. They sold to seven buyers around 1 448.116 kilos and 6.349 different types of fish in average daily. Buyers are heterogenous, they came 266.81 days in average on the Boulogne-sur-Mer fish market. 600 kilos and 5 different types of fish are bought daily in average per buyer from 6 different sellers.

In what follows a detailed explanation of these results are given.

Heterogenous boats

Once on the dock, the arriving fishing boats unload the fish (the fishing take place at night). These boats (the sellers) have to make a choice each day. Either they decide to put the fish on the auction submarket, or they keep the fish on the boat and they decide to negotiate. Sellers cannot divide their fish daily because it is costly (Mignot (2012)). Figure A.1 represents the distribution of the number of selling days on the Boulogne-sur-Mer fish market. The Boulogne-sur-Mer fish market was opened 539 days from April 2006 till December 2007. The number of maximum days a seller visits this market was 464 days, and 1 day as the minimum. Sellers are not present every day. Their presence depends on their size and the boat's type. Two types should be characterised : the small-scale fisheries (that go into water for less than 24 hours) and the coastal fishing boat (between 24h and 48 hours).

The boat came to the Boulogne-sur-Mer fish market in average 152 days from April 2006 till December 2007 (see table A.3).

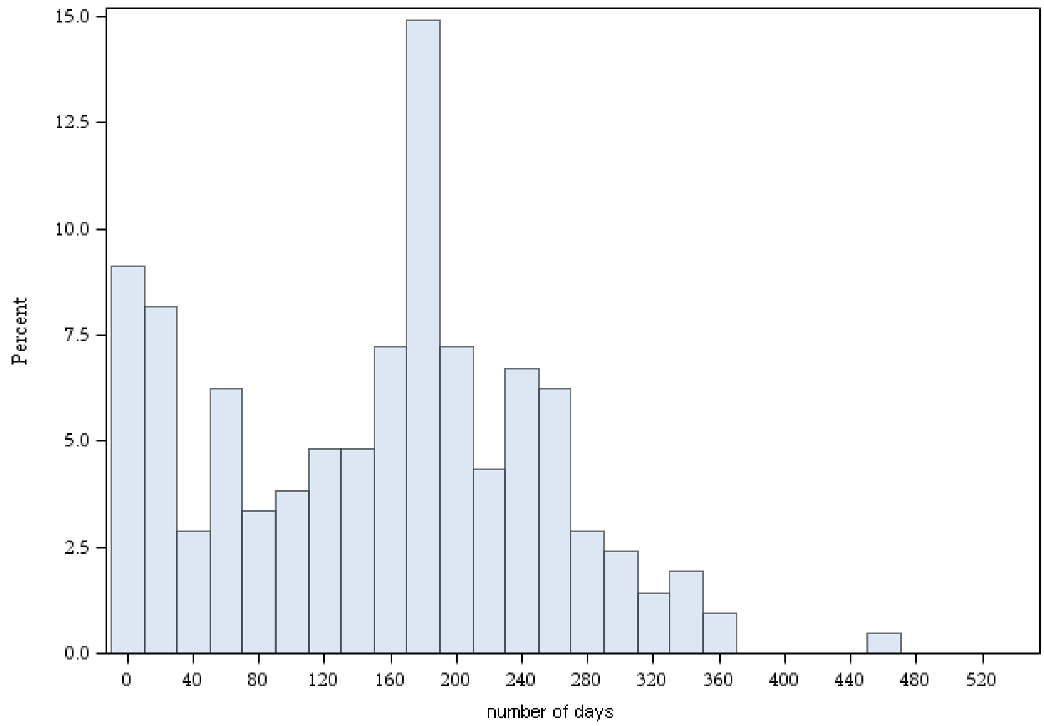


FIGURE A.1 – The distribution of the number of days, sellers are present on the Boulogne-sur-Mer fish market

N	208
Mean	152.187
Std Dev	97.195
Skewness	0.106
Kurtosis	-0.603

TABLE A.1 – Descriptive statistics for the number of presence day on the Boulogne-sur-Mer market

Figure A.4 represents the same distribution (the numbers of days) for the auction (left) and for the negotiated submarket.

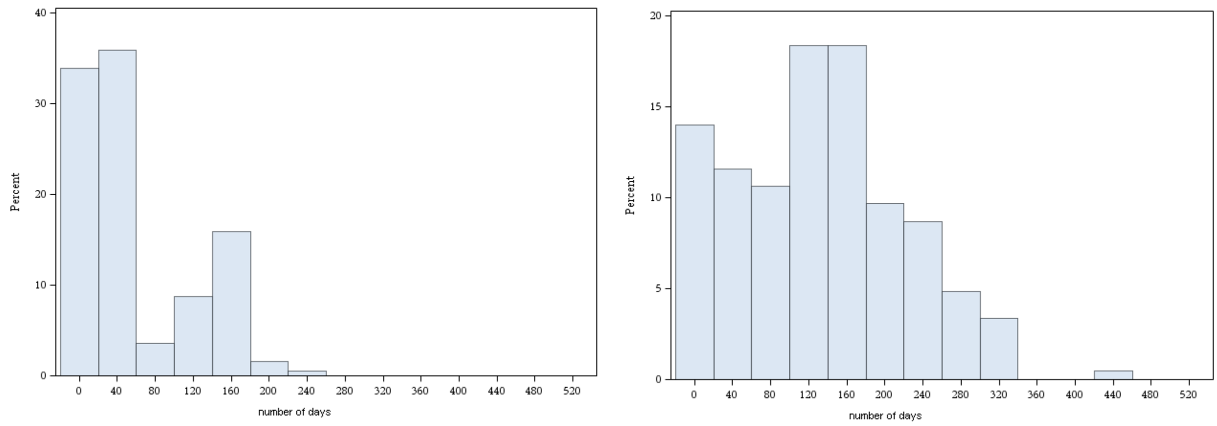


FIGURE A.2 – The distribution of the number of days, sellers are present on the auction (left) and negotiated (right)

	Auction	Negotiated
N	195	207
Mean	56.49	131.08
Std Dev	59.04	87.91
Skewness	1.01	0.39
Kurtosis	-0.46	-0.33

TABLE A.2 – Descriptive statistics of the distribution of the number of days on the auction and negotiated submarkets

As mentioned before, most of the sellers choose one market each day. Figure A.4 and table A.4 represent the number of days sellers auctioned or negotiated.

The Boulogne-sur-Mer fish market is the most important fish market in terms of quantity.

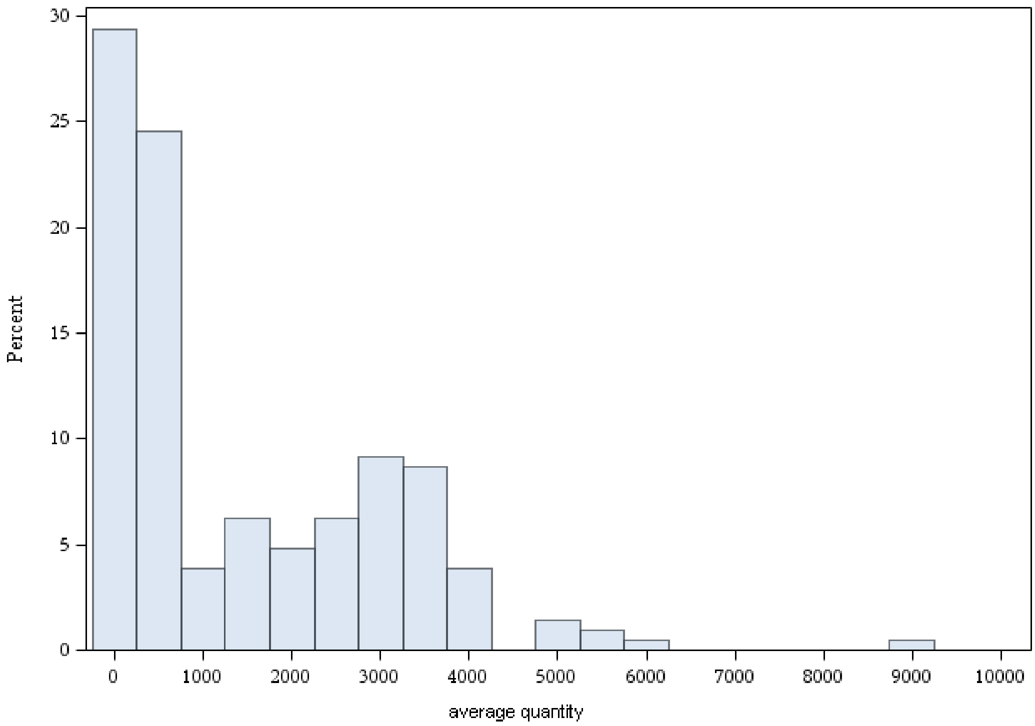


FIGURE A.3 – The distribution of the quantity of fish sold by boat in average each day on the Boulogne-sur-Mer fish market

1 448 kilos are sold by boat in average each day.

N	208
Mean	1448.116
Std Dev	1545.537
Skewness	1.265
Kurtosis	1.963

TABLE A.3 – Descriptive statistics of the quantity daily sold by boat on the Boulogne-sur-Mer fish market

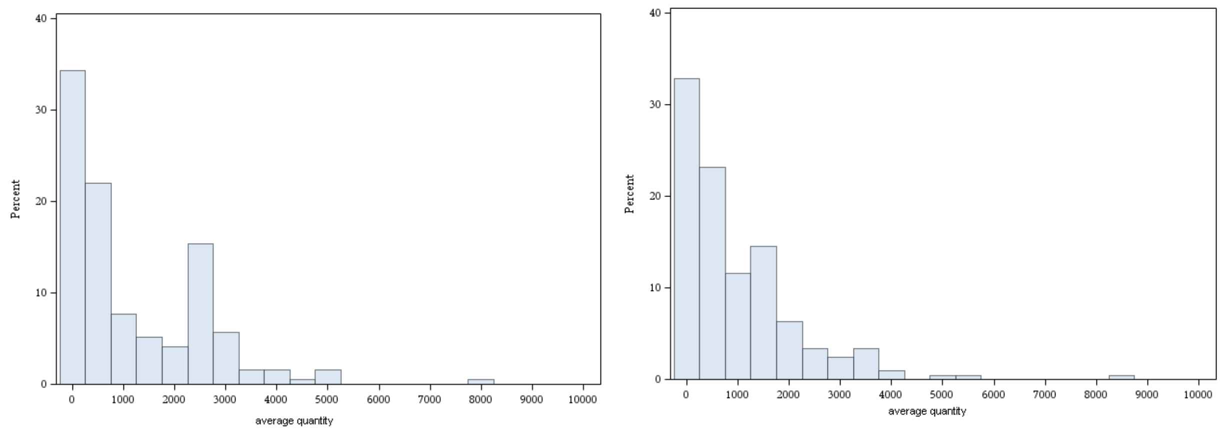


FIGURE A.4 – The distribution of the quantity sold by boats on the auction (left) and negotiated (right) in average per day

	Auction	Negotiated
N	195	207
Mean	1181.191	1000.384
Std Dev	1298.244	1155.225
Skewness	1.551	2.363
Kurtosis	3.506	8.622

TABLE A.4 – Descriptive statistics of the distribution of the quantity sold by boats on the auction (left) and negotiated (right) in average per day

As previously mentioned, the quantity sold on the auction submarket and on the negotiated submarket are quite similar. In average 1181 kilos are auctioned daily by boats and 1000 are negotiated.

Six different types of fish are sold in average by a boat daily. Figure A.5 and table A.5 picture the number of species sold by a boat on the Boulogne-sur-Mer fish market. Six species are sold daily by boat on the whole market.

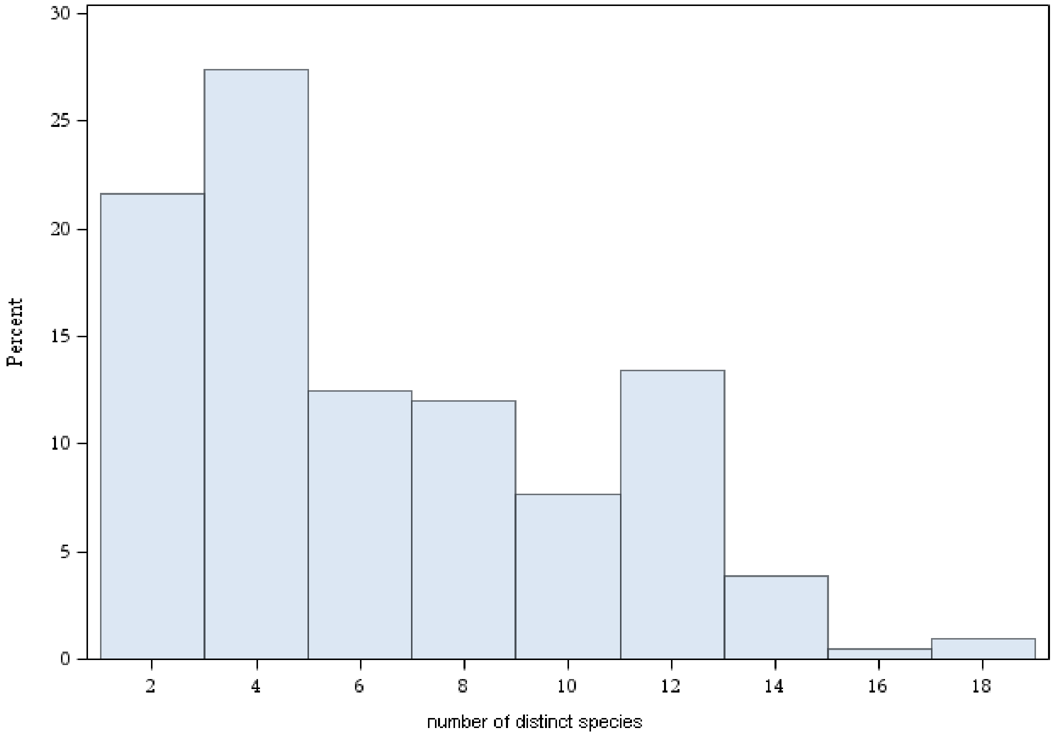


FIGURE A.5 – The distribution of the number of types of fish sold by boat in average each day on the Boulogne-sur-Mer fish market

N	208
Mean	6.349
Std Dev	4.007
Skewness	0.649
Kurtosis	-0.587

TABLE A.5 – Descriptive statistics for the number of distinct species on the Boulogne-sur-Mer market

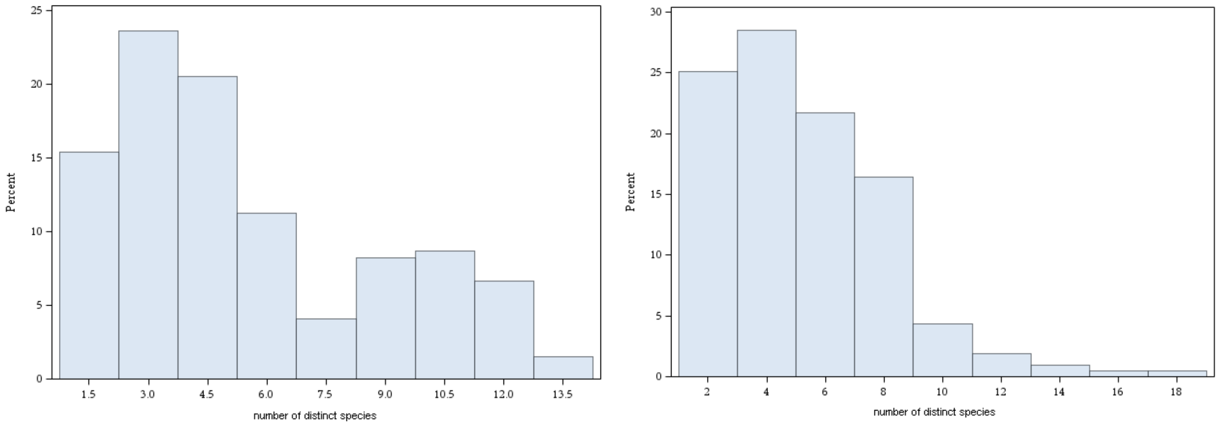


FIGURE A.6 – The distribution of the number of types of fish sold by boat in average each day on the auction (left) and negotiated (right) in average per day

	Auction	Negotiated
N	195	207
Mean	5.476	5.193
Std Dev	3.349	2.974
Skewness	0.694	1.065
Kurtosis	-0.734	1.792

TABLE A.6 – Descriptive statistics of the distribution of the number of types of fish sold by boat in average each day on the auction and negotiated in average per day

Figure A.8 and table A.6 show the distribution of the number of species caught and sold by a boat daily on each submarket. Five different types of fish are sold on each submarket per boat daily. No difference can be noted among the two selling mechanisms.

Finally, how many buyers are connected to a seller ?

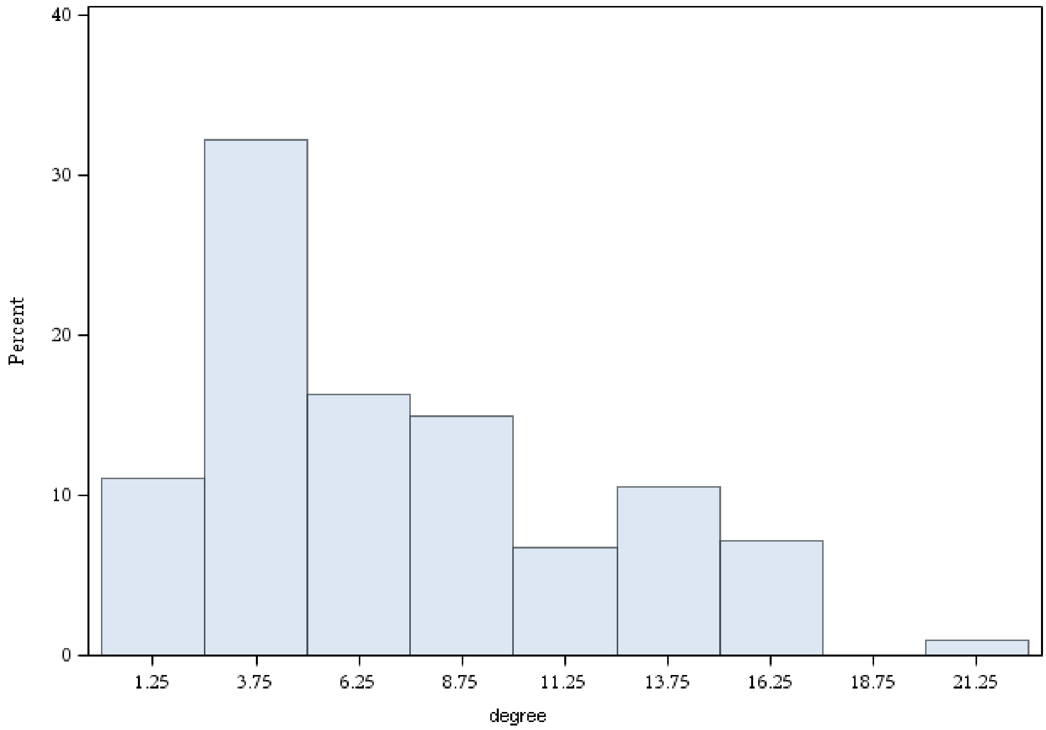


FIGURE A.7 – The distribution of the number of buyers connected to a boat in average each day on the Boulogne-sur-Mer fish market

Seven buyers are connected to a boat in average daily.

N	208
Mean	7.268
Std Dev	4.602
Skewness	0.774
Kurtosis	-0.407

TABLE A.7 – Descriptive statistics for the number of connected buyers on the Boulogne-sur-Mer market

On each submarket, the number of connected buyers to a seller is given in table A.8 and figure A.8.

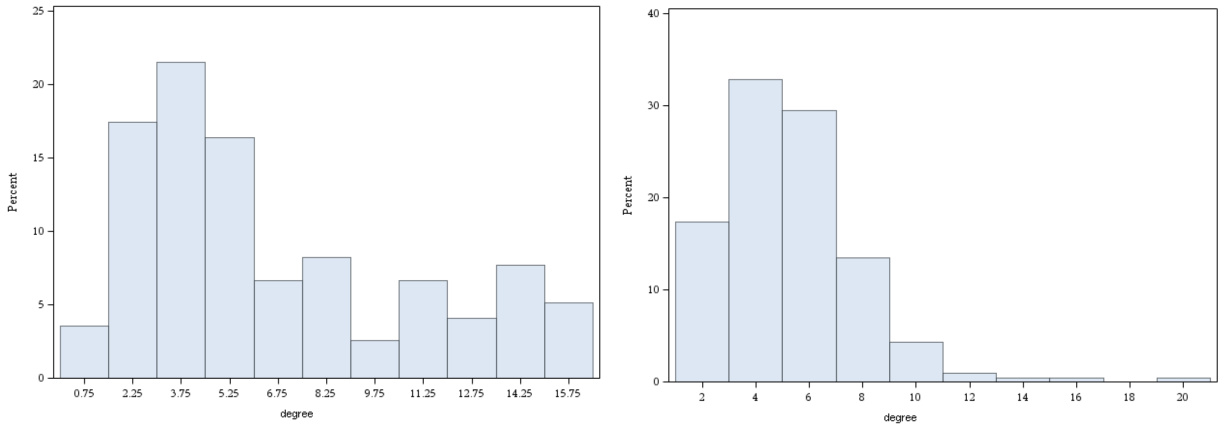


FIGURE A.8 – The distribution of the number of connected buyers to a boat in average each day on the auction (left) and negotiated (right) in average per day

	Auction	Negotiated
N	195	207
Mean	6.626	5.304
Std Dev	4.335	2.727
Skewness	0.796	1.531
Kurtosis	-0.651	4.974

TABLE A.8 – Descriptive statistics of the distribution of the sellers degree on the auction and negotiated in average per day

Heterogenous buyers

The buyers should be registered in order to enter the Boulogne-sur-Mer fish market. The 100 buyers registered came in average 267 days from April 2006 till December 2007. Buyers are heterogeneous, some of them are daily present on the market but other came for example less than 40 days.

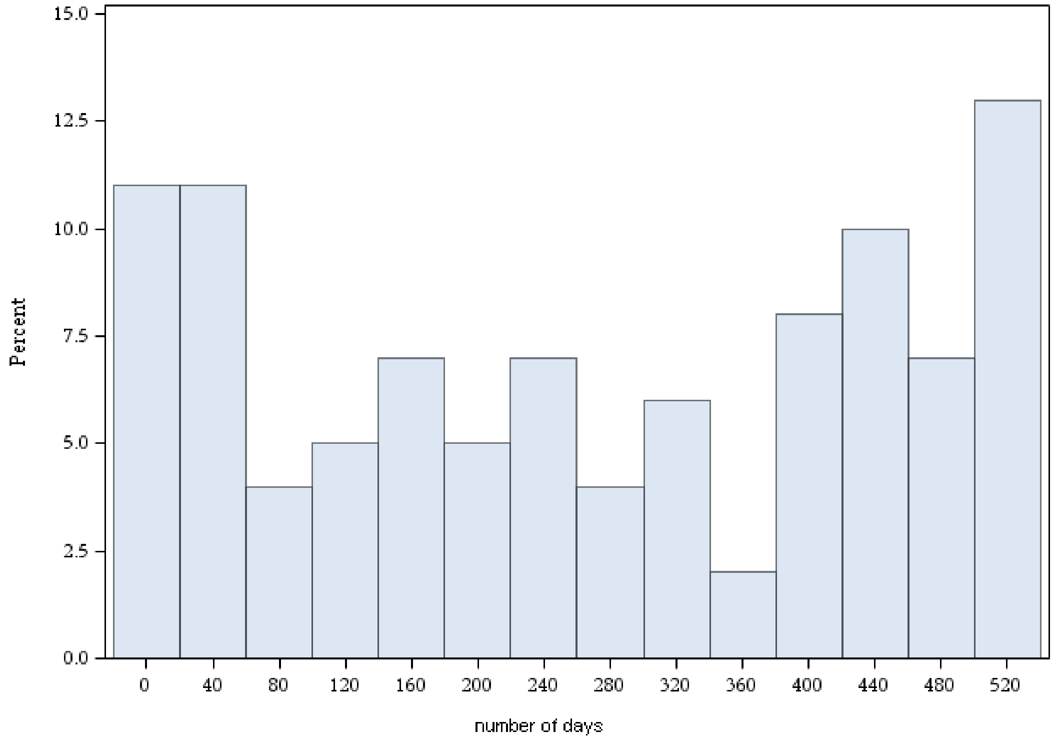


FIGURE A.9 – The distribution of the number of days, buyers are present (transact) on the Boulogne-sur-Mer fish market

N	100
Mean	266.81
Std Dev	184.977
Skewness	-0.031
Kurtosis	-1.469

TABLE A.9 – Descriptive statistics for the number of presence day on the Boulogne-sur-Mer market

Buyers are not like the sellers. They can switch among submarkets daily. Figure A.10 and table A.10 prove this.

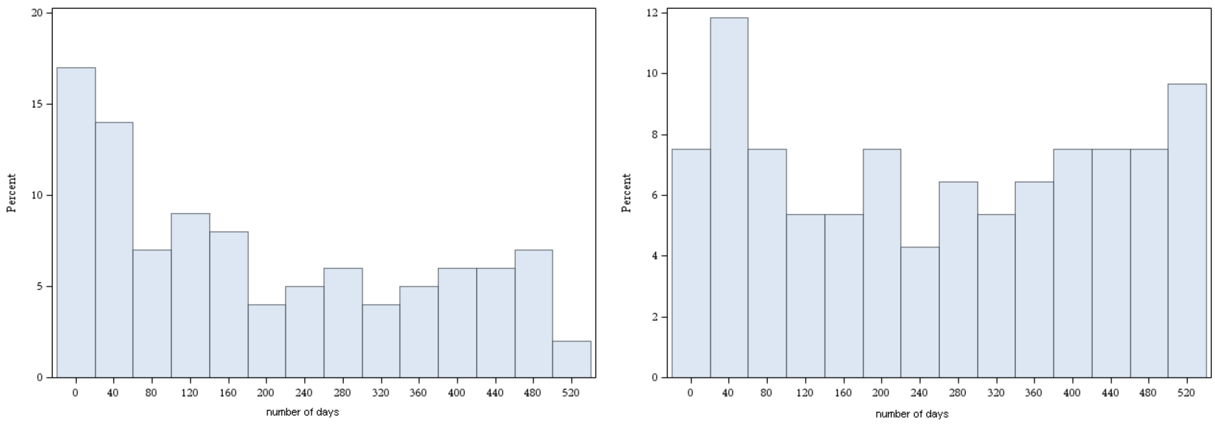


FIGURE A.10 – The distribution of the number of days, buyers are present on the auction (left) and negotiated (right)

	Auction	Negotiated
N	100	93
Mean	196.83	258.645
Std Dev	167.988	163.343
Skewness	0.459	0.010
Kurtosis	-1.207	-1.397

TABLE A.10 – Descriptive statistics of the distribution of the number of days on the auction and negotiated submarkets

Table A.11 and figure A.11 picture the distribution of the quantity bought by a buyer daily on the auction and the negotiated submarket. The value of the abscise axis are up to 6000 kilos per days. Therefore buyers are not similar. There are just few ones that can be called the big one. Most of them can be called the small ones and the other can be called the medium ones.

Buyers behave similarly on both designs when it comes to quantity : the big ones on the auction are big ones on the negotiated etc.

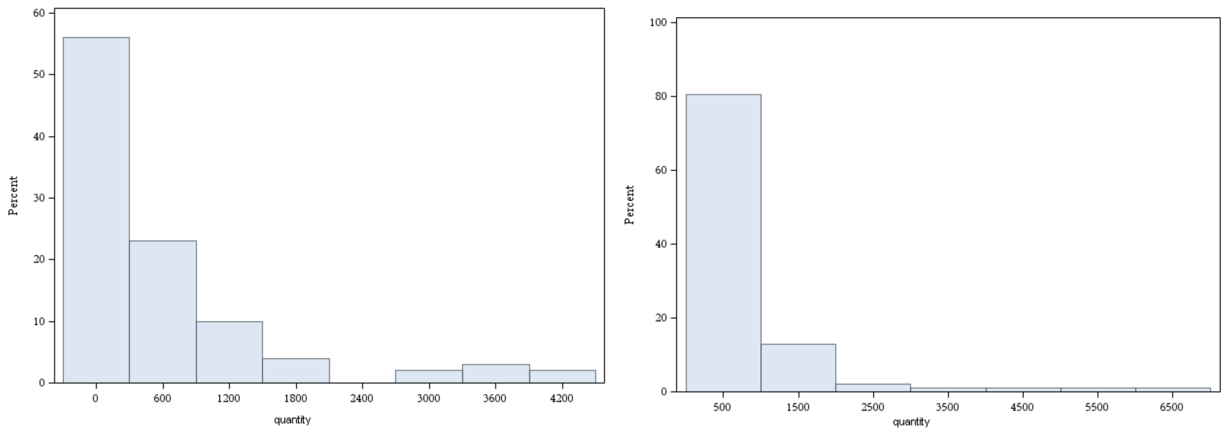


FIGURE A.11 – The distribution of the quantity bought bu the buyers on the auction (left) and negotiated (right) in average per day

	Auction	Negotiated
N	100	93
Mean	637.703	667.105
Std Dev	949.396	1096.123
Skewness	2.509	3.624
Kurtosis	5.979	15.451

TABLE A.11 – Descriptive statistics of the distribution of the quantity bought by the buyers on the auction (left) and negotiated (right) in average per day

The same thing goes for the number of species purchased daily by a buyer.

Five different types of fish are bought in average by a buyer daily. Figure A.12 and table A.12 picture the number of species sold by a boat on the Boulogne-sur-Mer fish market. Buyers are heterogenous, the number of species goes up to 16 species per day. 50% of the buyers purchase around 4.5 species (median). Buyers are different !

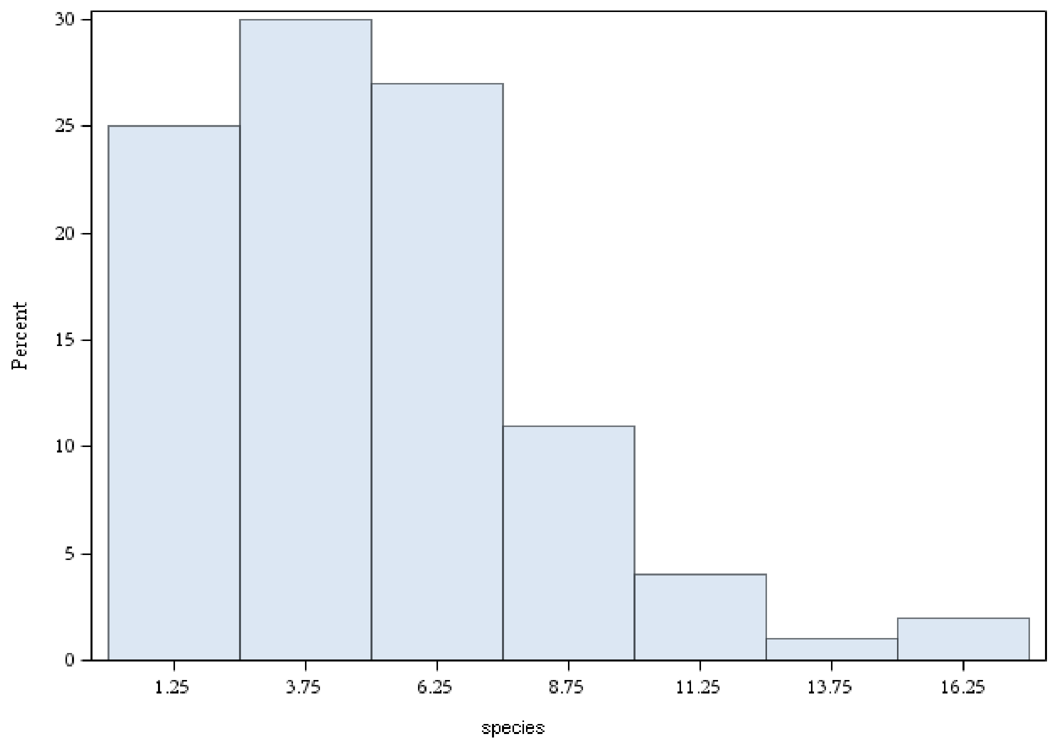
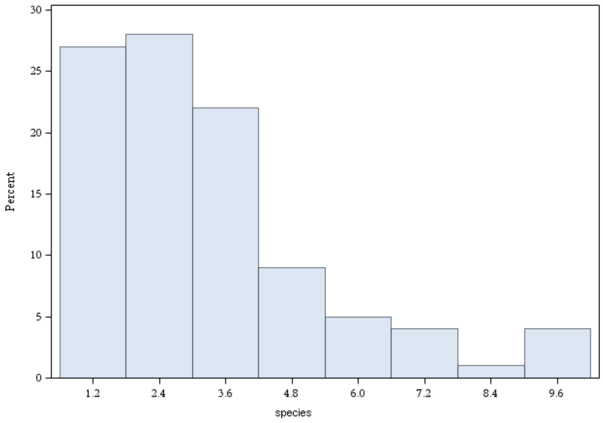


FIGURE A.12 – The distribution of the number of types of fish bought by buyer in average each day on the Boulogne-sur-Mer fish market

N	100
Mean	4.928
Std Dev	3.255
Skewness	1.115
Kurtosis	1.460

TABLE A.12 – Descriptive statistics for the number of distinct species on the Boulogne-sur-Mer market per buyer daily



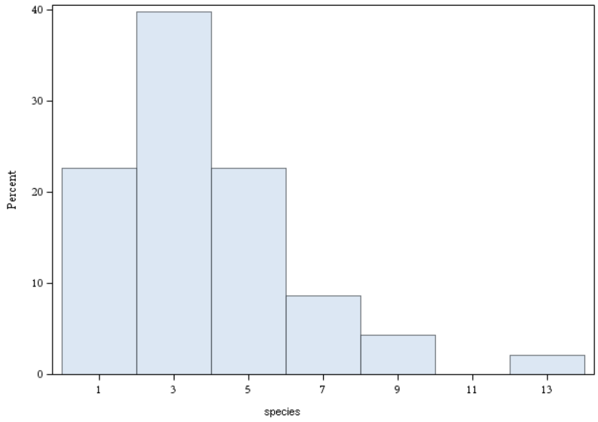


FIGURE A.13 – The distribution of the number of types of fish bought by a buyer in average each day on the auction (left) and negotiated (right) in average per day

	Auction	Negotiated
N	100	93
Mean	3.288	3.922
Std Dev	2.092	2.441
Skewness	1.355	1.444
Kurtosis	1.678	2.692

TABLE A.13 – Descriptive statistics of the distribution of the number of types of fish bought by a buyer in average each day on the auction and negotiated in average per day

Finally, how many sellers are connected to a buyer each day ?

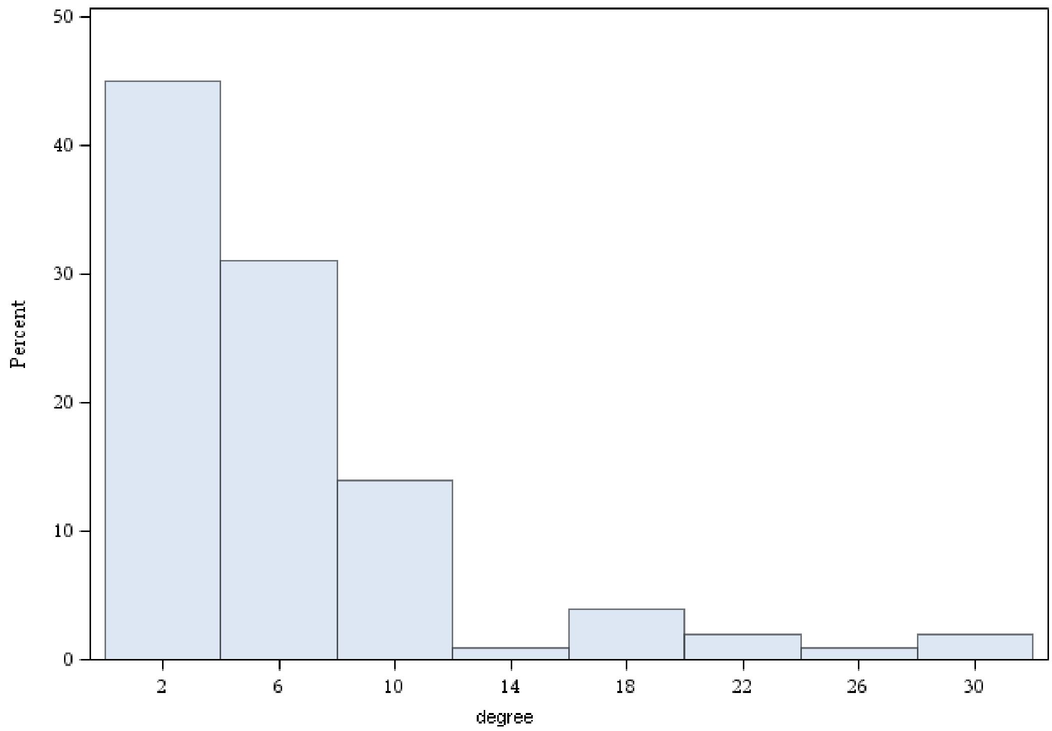


FIGURE A.14 – The distribution of the number of sellers connected to a buyer in average each day on the Boulogne-sur-Mer fish market

Six buyers are connected to a seller in average daily.

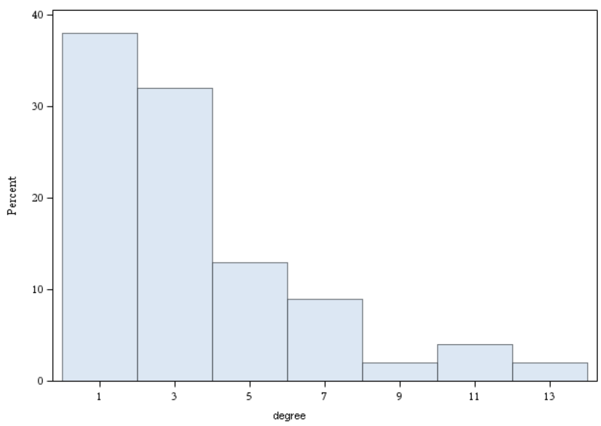
N	100
Mean	6.231
Std Dev	5.799
Skewness	2.195
Kurtosis	5.452

TABLE A.14 – Descriptive statistics for the number of the buyers' degree on the Boulogne-sur-Mer market

Figure A.15 and table A.15 represent the buyers' degree on the auction and on the negotiated submarket.

	Auction	Negotiated
N	100	93
Mean	3.556	4.418
Std Dev	2.743	3.908
Skewness	1.589	2.474
Kurtosis	2.276	6.991

Table A.15 – Descriptive statistics of the distribution of buyers' degree in average each day on the auction and negotiated in average per day



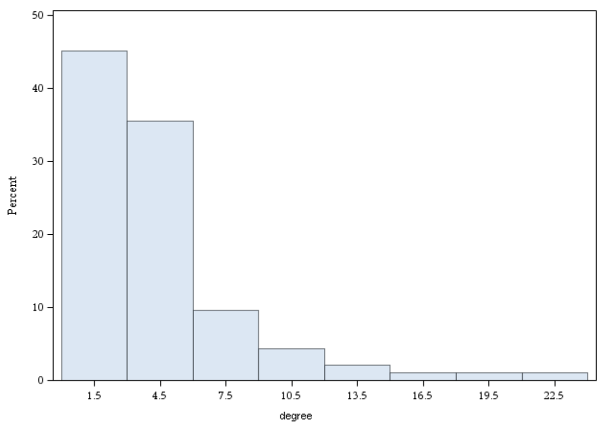


Figure A.15 – The distribution of the number of connected sellers to a buyer in average each day on the auction (left) and negotiated (right) in average per day

Not only the buyers and the sellers are heterogenous, the fish sold are quite different.

Heterogenous species

Seventy six different types of fish are sold on the Boulogne-sur-Mer fish market. The prices vary tremendously. Figure A.16 represents the distribution of the daily average prices per species.

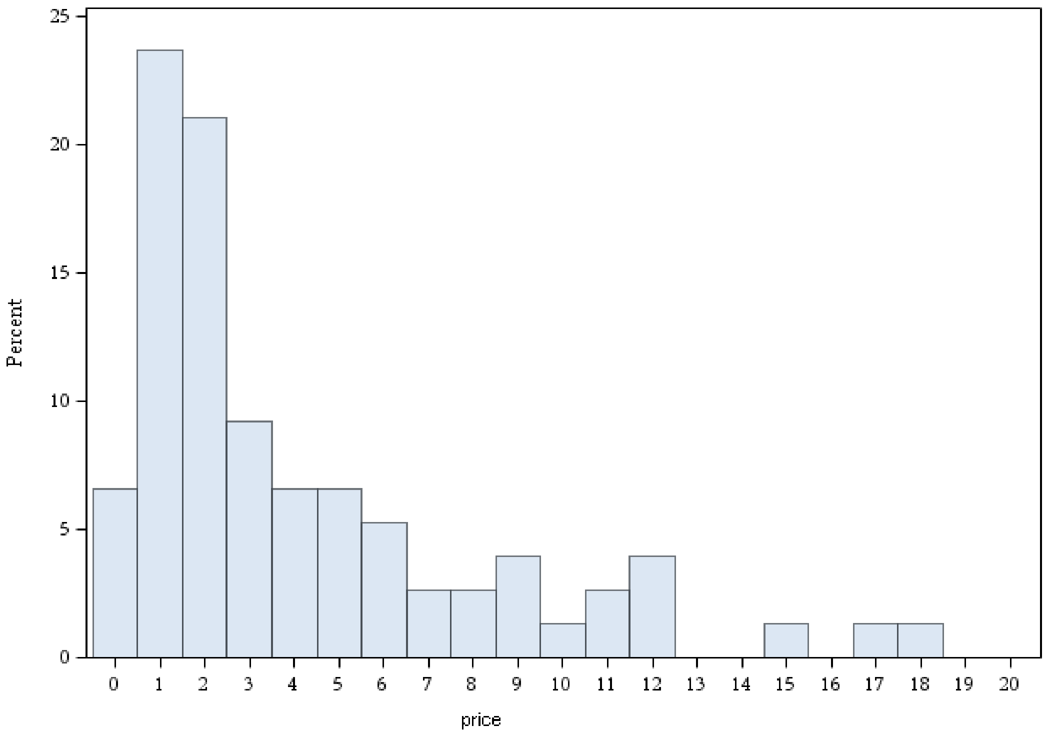


FIGURE A.16 – The distribution of the daily average price species by species on the Boulogne-sur-Mer fish market

Fifty percent of the different types of fish are sold for 2.483 euros per kilo. There are some kinds that are sold for 18 euros per kilos and others for 0.1 euros per kilos per day in average! For example the fish-id number "43010" in the database was sold for for 42 euros/kilo on December 28, 2006 and for 0.3 euros/kilo and 38 euros/kilo on December 21, 2007 (see figure A.17).

N	76
Mean	4.147
Std Dev	4.074
Skewness	1.544
Kurtosis	1.966
Median	2.483

Table A.16 – Descriptive statistics for the prices per species

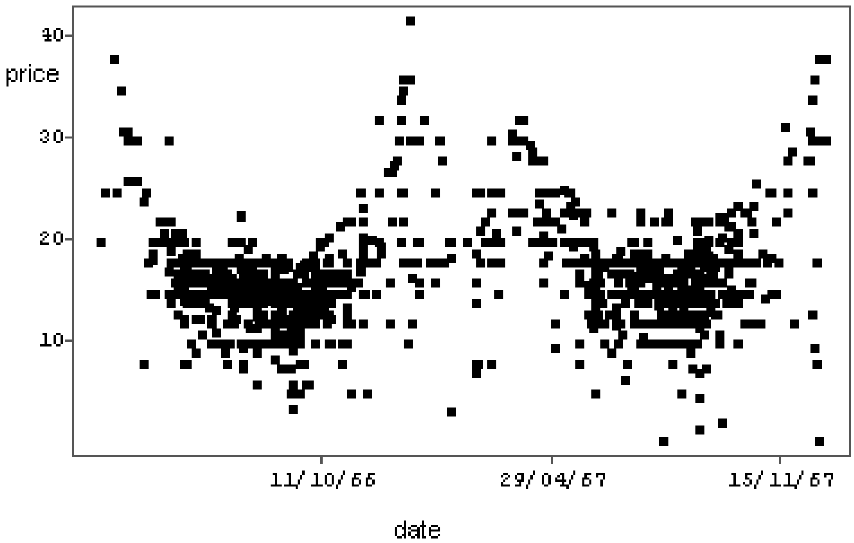


Figure A.17 – The Scatter plot for all the prices for the "43010" fish

Figure A.18 represents the distribution of the total quantity species by species sold over all the period on the Boulogne-sur-Mer fish market and its logarithm. The median of the left distribution is 12 701.80 kilos the maximum stands for 9 026 662.10 kilos and the minimum for 2 kilos. The mean is 570 447.204 kilos and the standard deviation is important (1 363 138.8 kilos).

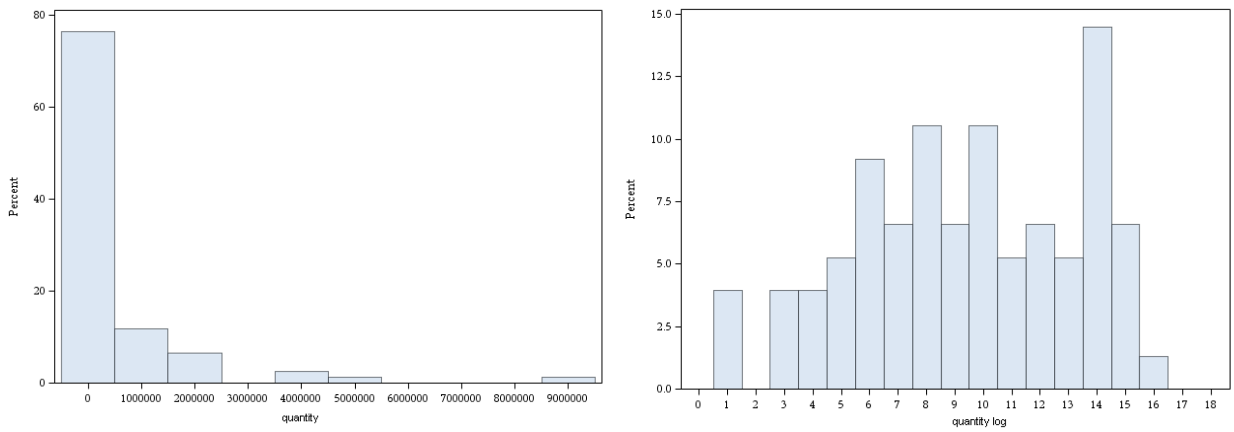


FIGURE A.18 – The distribution of the quantity per species and the logarithm of the quantity per species from April 2005 until December 2006

1 310 of kilos are sold daily on the Boulogne-sur-Mer fish market per species. That standard deviation of the distribution for figure A.19 is equal to 2788.72. The skewness stands for 3.58 and the kurtosis for 15.64. Moreover 128.88 kilos are sold daily for half of the fish type.

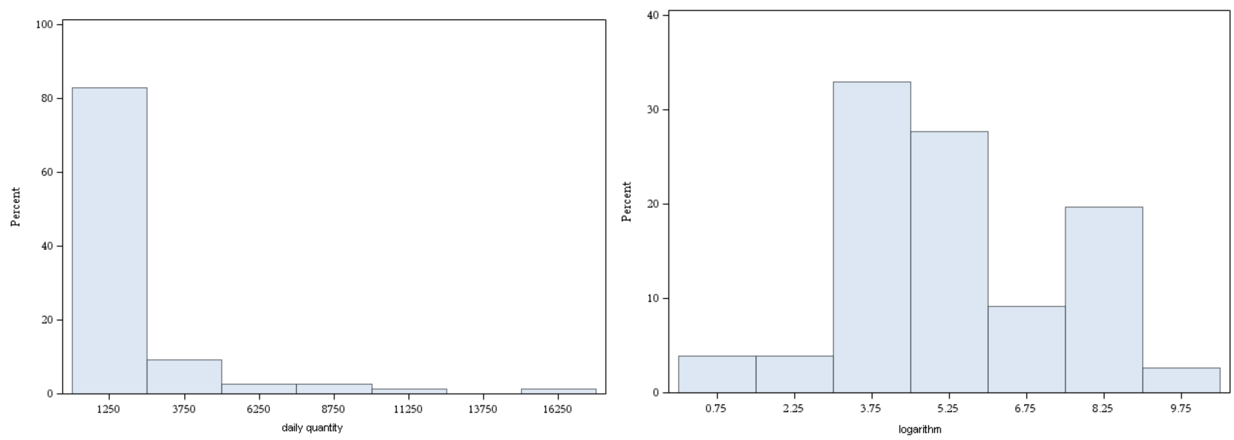


FIGURE A.19 – The distribution of the daily quantity per species and its logarithm

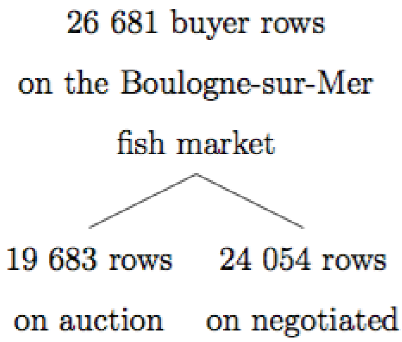
B General Appendices

B.1 Buyers' switching

A buyer (or a seller) has the possibility to choose where to go. He can pick up on submarket or he can switch between submarkets daily. Do sellers divide their fish between submarkets daily ? Or do they sell all of their catching on one submarket ? For comparison, figures B.1 and B.2 show the distribution of the ratio between the number of day buyer i (seller j) switched between submarkets daily over the number of days he came on the Boulogne-Sur-Mer fish market (left distribution) ; and the distribution of the number of daily switching days (right distribution) (See appendix B.3). To do so, we list for each buyer (seller) for each submarket, the days on which they purchased (sold), then we count the number of mutual day (switching days).

Each day, buyers have the possibility to purchase on one or on both submarkets. Each row represents a distinct day of transactions for a distinct buyer on the BsM. The 100 buyers enter the Boulogne-sur-Mer fish market 26 681 times (26 681 rows). From these 26 681 times, 19 683 are on auction and 24 054 are off auction. Thus, many buyers switch between submarkets the same day. They represent 17 056 distinct rows (64% of total rows). In sum, 90 buyers from the 100 moved at least one day (one time) from a submarket to the other.

For the 100 buyers, the ratio mean is equal to 0.48 with a standard deviation of 0.28, what explains that half of the time, buyers go to both submarkets. This is also showed by the mean of "*day*" equals to 170.56 with a standard deviation of 162 ! This explains more the buyers heterogeneity and that buyers are not the same and have different preferences. Moreover, the correlation between the number of day a buyer enter the BsM and the number of daily switching is equal de 0.9 (<.0001). That is, there is clearly a significant positive correlation. Buyers who come more regular on the BsM, alter between submarkets.



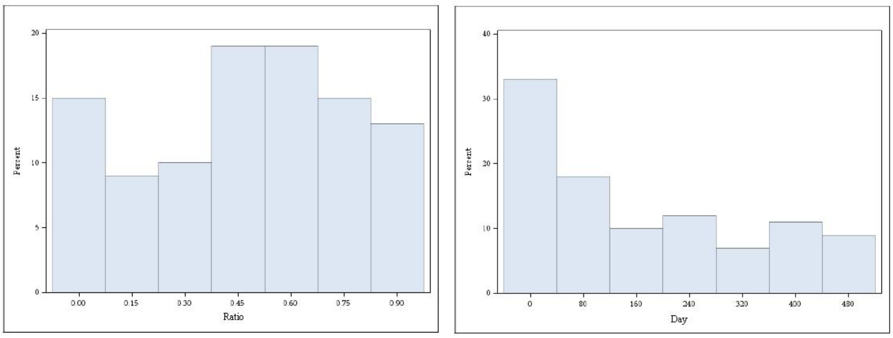
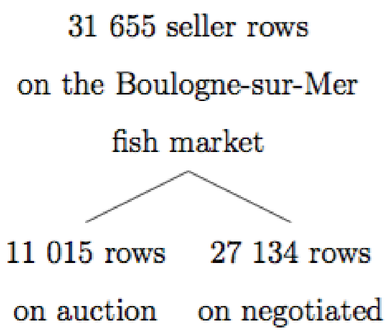


FIGURE B.1 – Distribution of the ratio and the number of mutual day from the buyer side.

B.2 Sellers' switching

For the 208 buyers, they enter on the Boulogne-sur-Mer fish market 31 655 times (rows). From these 31 655 times, 11 015 are for the auction submarket and 27 134 are for the negotiated. Sellers might also sell their fish on both submarkets daily. They represent 6 494 rows. In sum, 184 from 208 sellers went at least one day on both submarkets. But just few sellers go to both submarket avery day (see Figure B.2 [1]). As for the correction between the switching days and the coming days, the coefficient is equal de -0.02 and it is not significant. Hence, no relation between the number coming days and the switching days.



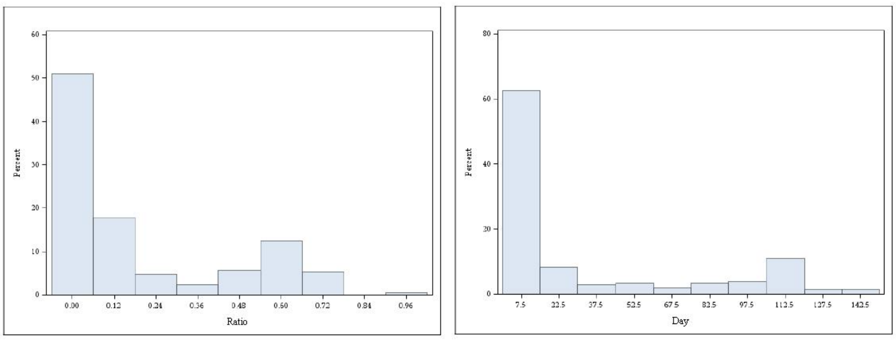


FIGURE B.2 – Distribution of the ratio and the number of mutual day from the seller side.

Do sellers divide their catching in terms of quantity between submarkets if they decided to switch daily ? In what follows, we look at the quantity exchanged the days which sellers

1. ratio distribution : the mean is equal to 0.19 and standard deviation 0.24 - day distribution : mean = 31.22 and standard deviation=42.66

visit both designs. The following ratio is computed : $\frac{q_{st}}{Q_{st}}$ (see figureB.3[2]) , where Q_{st} represents the total quantity that a seller sold on the BsM and q_{st} the quantity sold on the non-priority submarket (the submarket where the seller decides not to sell his big part of catching).

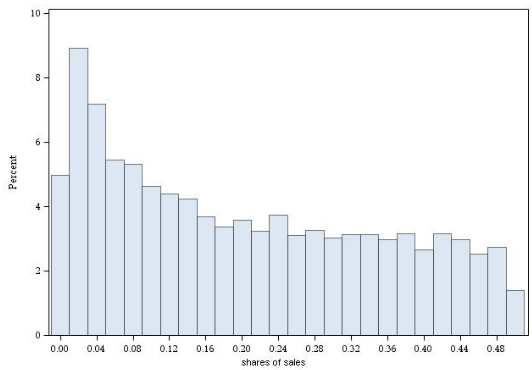


FIGURE B.3 – Distribution of the shares of the sales for the mutual days

As shown in figure B.4, sellers do not tend to switch frequently between submarkets in order to divide their catching. The ones who really divide their catching (quantity ratio=0.5) are the one one who rarely switch. The one who switch frequently share their fish between the submarkets (with 75%, 25%).

2. For the 6494 observations, the mean=0.20, standard deviation= 0.15, Skewness=0.37 and kurtosis=-1.15

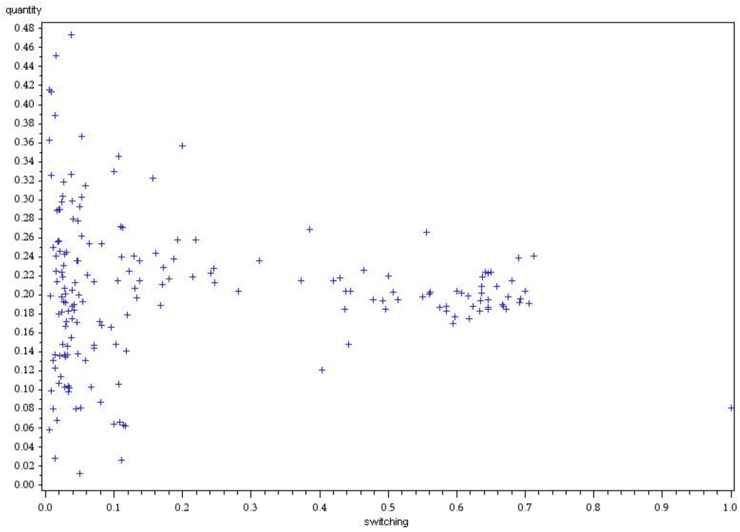


FIGURE B.4 – Plot between the switching ratio and the non-priority market in term of quantity

B.3 Buyers and sellers presence

Buyers and sellers are free to choose between both structures. Figures B.5 and B.6 show the distribution of the number of days buyers [sellers] purchase [sell] fishes on each submarket.

The average exchanging days on the negotiated submarket [auction] for buyers is 258.64 [196.83] with a standard deviation of 173.34 [167.99]. As for the sellers, they negotiated [auctioned] fishes in average 131.08 days [56.49] with a standard deviation of 87.91 [59.04].

Buyers and sellers do not came with the same frequency on both designs. Some of them came very frequently to The BsM market and to each submarket and other not.

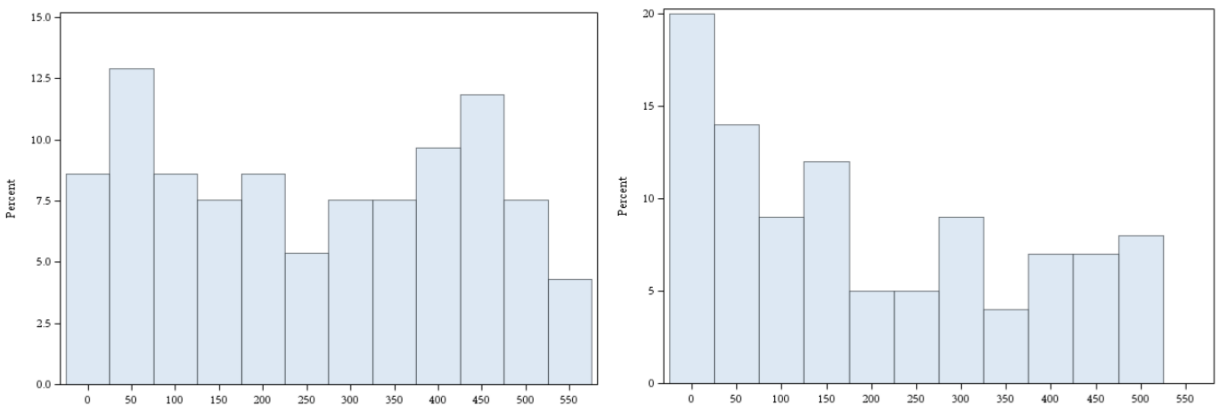


FIGURE B.5 – Distribution of the number of presence day for N buyers on negotiated [left] and auction [right] submarkets.

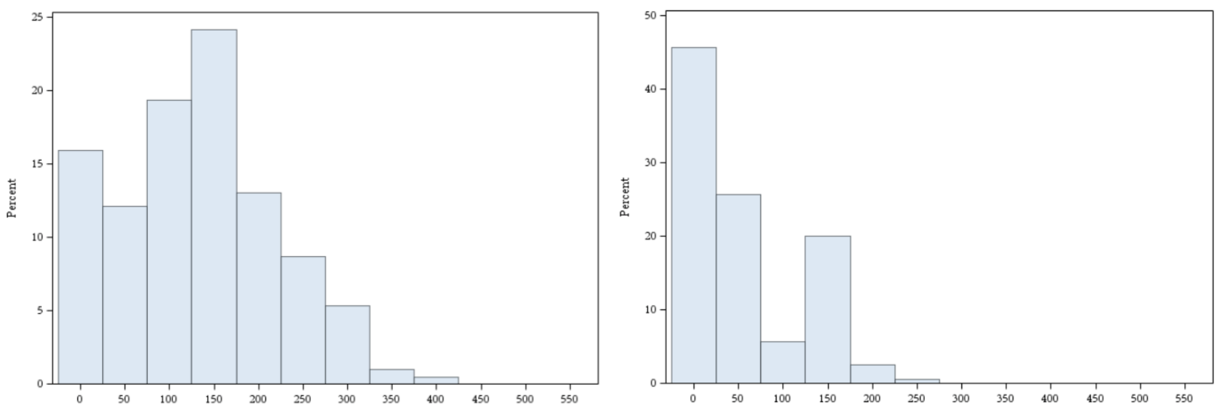


FIGURE B.6 – Distribution of the number of presence day for M sellers on negotiated [left] and auction [right] submarkets.

B.4 Sellers' preference to a market

Consider for each seller j with j=1 ... M :

- d_j^{auct} as the number of days a seller j is present on the auction market
- d_j^{neg} as the number of days a seller j is present on the negotiated market

For the 208 boats that visit the Boulogne-sur-Mer fish market, we define for each one :

$$\Delta_j^d = d_j^{auct} - d_j^{neg} \tag{B.1}$$

as the difference between the number of day, boat j sells his fish on the auction and negotiated submarkets.

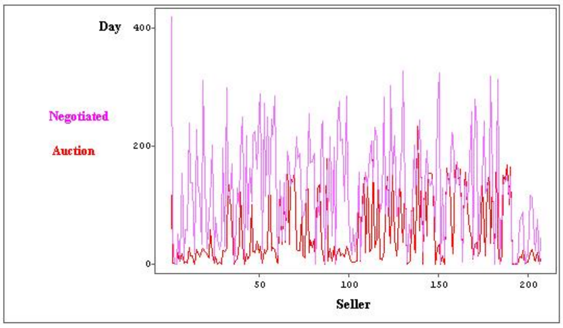


FIGURE B.7 – Line plot for seller presences on both submarkets.

Figure B.7 shows how many days each seller (id 1-200) is present on the auction (red line) and the negotiated (purple line) submarkets. As we can see in Figure B.7, sellers do not go the both submarkets at the same frequency. Some of them have some preferences to one submarket more than the other.

The distribution of equation B.1 is presented in Figure B.8. The mean of Δ_j is negative (see Table B.1). This negative mean affirms us that boats intended to choose more the negotiated submarket to unload fish.

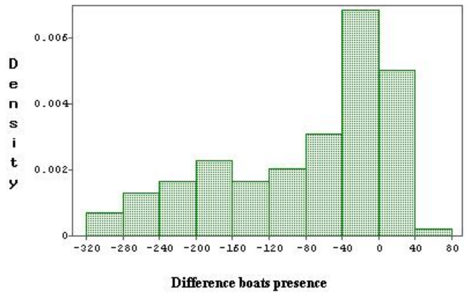


FIGURE B.8 – Distribution of the difference between the number of days a sellers is present on the auction and on the negotiated submarkets.

N	208
Mean	-77.49
Std Dev	93.63
Skewness	-0.75
Kurtosis	-0.71

TABLE B.1 – Descriptive statistics for the boats difference between the number of presence day on auction and negotiated submarket

B.5 Buyers' preference to a market

Consider for each buyer i, where i= 1 ... N

- d_i^{auct} as the number of days a buyer i is present on the auction submarket
- d_i^{neg} as the number of days a buyer i is present on the negotiated submarket

Figure B.9 pictures the buyers presence on each submarket. At a first sight, buyers intended to visits both submarkets (see Figure B.9) at the same frequency. But statistical tests show that this is not the case. The ttest zero mean shows that buyers do not have the same preferences to both submarkets (see Table B.2).

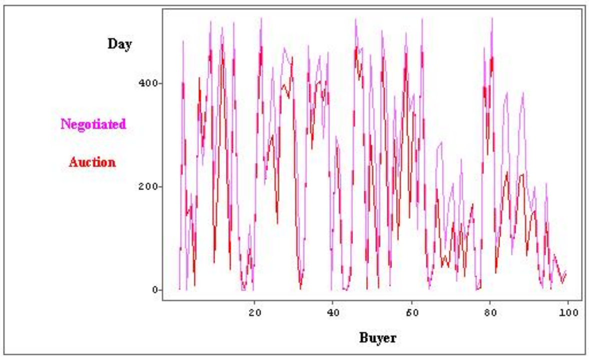


FIGURE B.9 – Line plot for the buyer presence on both submarkets.

Test	t value	Pr > |t|
ttest	-6.84	<.0001

TABLE B.2 – Ttest zero mean

We computed for each buyer :

$$\Delta_i^d = d_i^{auct} - d_i^{neg} \tag{B.2}$$

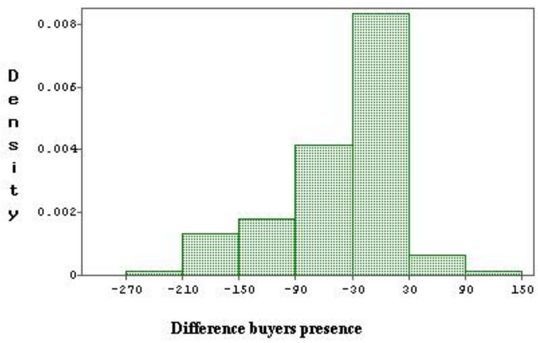


FIGURE B.10 – Distribution of the buyer difference presence.

As depicted in Figure B.10 and in Table B.3, the negative mean of Δ_i^d indicates that the negotiated submarket is more visited by the buyers.

N	100
Mean	-43.71
Std Dev	63.89
Skewness	-0.72
Kurtosis	1.1

TABLE B.3 – Descriptive statistics for the buyers difference between the number of presence day on auction and negotiated submarket

B.6 Couples' preference

For each formed couple (i, j) denote :

- m_{ij}^{auct} as the number of the days a couple (i, j) meets and transacts on the auction submarket
- m_{ij}^{neg} as the number of the days a couple (i, j) meets and transacts on the negotiated submarket

We study the difference between the number of encounters on the auction submarket and the number of encounters on the negotiated one for each couple (i, j) formed on the Boulogne-sur-Mer fish market. We denote : Δ_{ij}^{enc} as the difference between the number of days a couple meets on the auction submarket m_{ij}^{auct} and the number of days the same couple meets on the negotiated one m_{ij}^{neg}.

$$\Delta_{ij}^{enc} = m_{ij}^{auct} - m_{ij}^{neg} \tag{B.3}$$

- A negative value for Δ_{ij}^{enc} shows that (i, j) transacts more days on the negotiated submarket.

- A positive value for Δ_{ij}^{enc} indicates that (i, j) transacts more days on the auction submarket.
- A zero value for Δ_{ij}^{enc} proves (i, j) is indifferent between both submarkets.

To better understand the couples behaviour on both submarkets, the distribution for Δ_{ij}^{enc} is pictured in figure B.11.

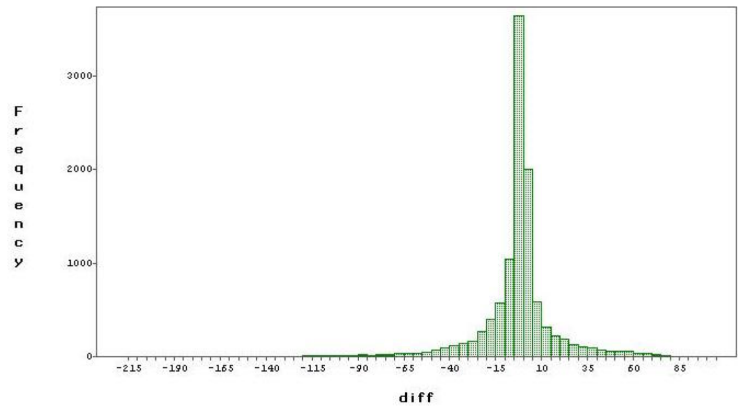


FIGURE B.11 – The distribution Δ_{ij}^{enc}

Mean	-3.912
Std Dev	24.26
Skewness	-1.54
Kurtosis	10.14

TABLE B.4 – Descriptive statistics for the distribution of Δ_{ij}^{enc}

The negative value of the mean in Table B.4 confirms that the repeated encounters take place more on the negotiated submarket than on the auction one. As so the negative value for the skewness proves that our distribution has more negative value. The kurtosis is higher than 3, our distribution is sharper than the normal one, with values concentrated around our negative mean.

More couples intended to visit the negotiated submarket and repeated encounters occur more often on the negotiated submarket.

B.7 Weighted couples' preference

In order to explain in deep agents choices for the meeting market point, we weighted the couples interaction by the number of presence day using the logarithm.

Consider for :

- Each seller j with j=1 ... M :
  - d_j^{auct} as the number of days a seller j is present on auction market
  - d_j^{neg} as the number of days a seller j is present on negotiated market
- Each buyer i, where i= 1 ... N
  - d_i^{auct} as the number of days a buyer i is present on auction submarket
  - d_i^{neg} as the number of days a buyer i is present on negotiated submarket
- Each couple (i, j)
  - m_{ij}^{auct} as the number of days a couple (i, j) meets and transacts on auction submarket
  - m_{ij}^{neg} as the number of days a couple (i, j) meets and transacts on negotiated submarket

$$D_{s,b} = \frac{m_{i,j}^{auction}}{d_i^{auction} * d_j^{auction}} - \frac{m_{i,j}^{negotiated}}{d_i^{negotiated} * d_j^{negotitated}} \tag{B.4}$$

To differentiate between a positive and a negative value when using the logarithm, we suppose that for every $D_{s,b} < 0$, the logarithm is defined as follow $-log(-D_{s,b})$.

The distribution of the logarithm for equation B.4 is pictured in figure B.12 and figure B.13. The difference between figure B.12 and figure B.13 is related to the couples that do not interact $(m_{i,j} = 0)$. We remove all these couples in figure B.13.

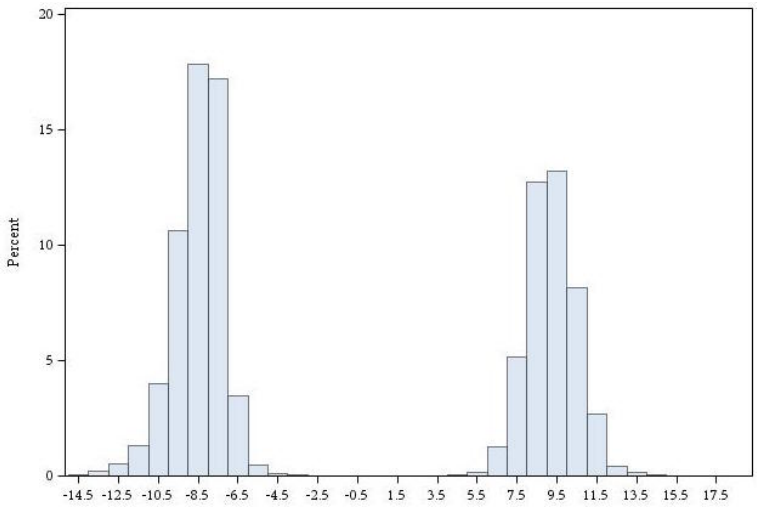


FIGURE B.12 – Distribution of the logarithm of weighted ratio (Equation B.4) for all the couples

Mean	-0.67
Median	-7.14
std Dev	8.89
Skewness	0.23
Kurtosis	-1.85

TABLE B.5 – Descriptive statistics of the logarithm of the weighted ratio (Equation B.4) for all the couples

As shown in figure B.12, our couples are divided into two obvious categories : the ones who transact on negotiated submarket and the ones who prefer auction one. The difference between the mean and the median (in table B.5) can be explained as follow :
As the median is smaller than the mean and both of them have negative values, we can conclude that couples have more repeated interactions on negotiated submarket than on auction one.

Mean	-4.24
Median	-7.88
std Dev	7.74
Skewness	1.17
Kurtosis	-0.44

TABLE B.6 – Descriptive statistics of the logarithm of the weighted ratio (Equation B.4) for chosen couples

We restrain our study and we choose our 6887 couples (defined in the upper section). Figure B.13 and table B.6 show more interesting results. The mean is also negative but it is higher than the one in table B.5.

This negative mean proves that repeated encounters between couples take place more on negotiated submarket. This can be related to the intensity of link between couples on negotiated submarket, where the information is hard to get and link are easier to create.

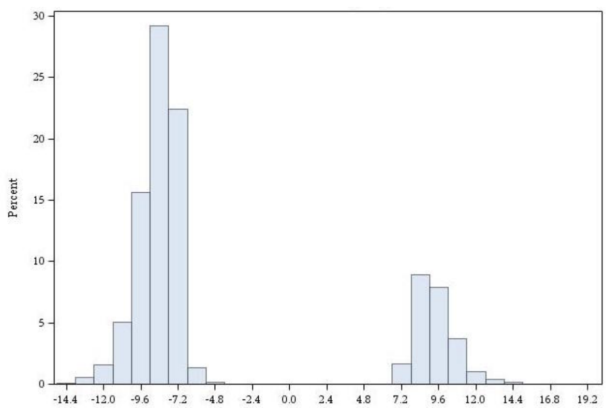


FIGURE B.13 – Distribution of the logarithm of weighted ratio (Equation B.4) for chosen couples

B.8 Couples' creation vs quantity

The number of couples formed each day on both submarkets can not be considered the same. Here, the percentage of couples formed every day on different market designs is calculated. This percentage gives an idea on the number of formed couples in order to compare for both submarkets if loyalty between agents is more present on one market more than the other. Loyalty is defined as follow :
Each day, every buyer considering his needs, has the possibility to meet and transact with one or more seller on each submarket. A loyal buyer buys from a few seller (that he chooses and he trusts) and therefore the number of formed couple over the number of potential couple should be lower on the submarket where loyalty emerges (the negotiated one).
Our ratio reflects the market's couple :

$$\text{Market's couple} = \frac{\text{the number of the couples formed}}{\text{the number of potential couples}} \tag{B.5}$$

Consider a market with i buyers with $i = 1...N$ and j sellers with $j = 1...M$ with $\tau = 1...t$

- N_τ^{auc} : the number of buyers i that are present and transact once or more on the auction submarket day τ ;
- N_τ^{neg} : the number of buyers i that are present and transact once or more on the negotiated submarket day τ ;
- M_τ^{auc} : the number of sellers j that are present and transact once or more on the auction submarket day τ ;
- M_τ^{neg} : the number of sellers j that are present and transact once or more on the negotiated submarket day τ ;
- C_τ^{auc} : the number of couples (i, j) formed on the auction submarket at a day τ ;
- C_τ^{neg} : the number of couples (i, j) formed on the negotiated submarket at a day τ ;
- $N_\tau^{neg} * M_\tau^{neg}$: the number of the potential couples on the negotiated submarket ;
- $N_\tau^{auc} * M_\tau^{auc}$: the number of the potential couples on the auction submarket.

We hence consider for each submarket every day, the *market's couple ratio* defined as follow :

$$Ml_{\tau}^{neg} = \frac{C_{\tau}^{neg}}{N_{\tau}^{neg} * M_{\tau}^{neg}} \tag{B.6}$$

$$Ml_{\tau}^{auct} = \frac{C_{\tau}^{auct}}{N_{\tau}^{acut} * M_{\tau}^{auct}} \tag{B.7}$$

Each point in Figure B.14 represent Ml_{τ}^{neg} and Ml_{τ}^{auct} for every τ.

We remark that our ratio on the negotiated submarket is concentrated for the values lower than 20%, unlike the auction submarket where the values are more dispersed and they can go up to 50%.

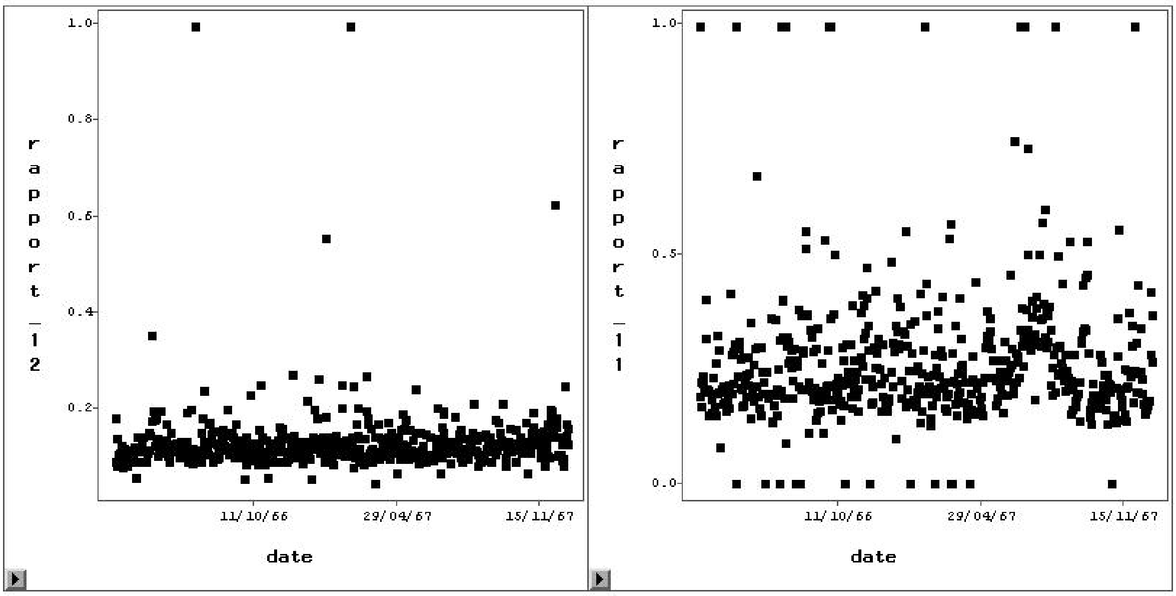


FIGURE B.14 – The number of couple formed over the number of potential couple each day at each submarket

We assume that a high ratio shows that most of the buyers transact in general most of the sellers, unlike a low ratio where there is not so many couples formed on the market. Hence, can we relate the link intensity to this ratio ? Our ratio can take value between 0 and 1. Value 1 shows that all the sellers transact with all the buyers, we can therefore assume that on a market where the value is nearer to 1, the market can be considered as a non loyal market. Otherwise, a market where the value is close to 0, only few couples are formed and therefore not all the agents meet. Loyalty can be considered more important.

Figure B.15 draws the distribution of the couple formed ratio on the auction and the negotiated submarkets. The mean on the auction submarket is double the one on the negotiated submarkets (see Table B.7).

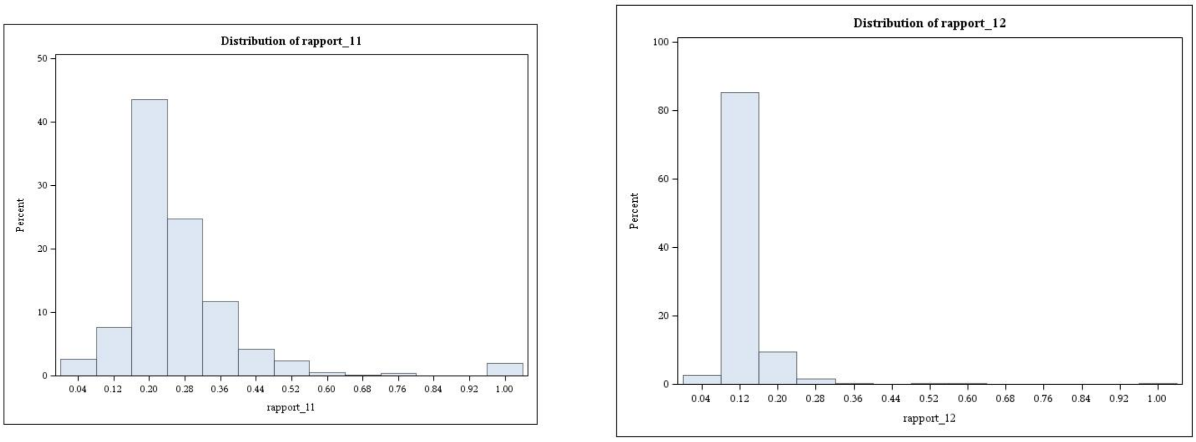


Figure B.15 – The distribution of Ml_{τ}^{auct} (left) and Ml_{τ}^{neg} (right)

	Auction	Negotiated
N	539	539
Mean	0.266	0.129
Variance	0.021	0.004
Skewness	2.738	8.731
Kurtosis	11.09	99.55

TABLE B.7 – Descriptive statistics of the distribution of the market's couple ratio on the auction and negotiated submarkets

In this study, we prove if this difference between the market's couple ratio is related to the quantities exchanged on each submarket. Do buyers meet with more sellers because they exchanged more quantities ? Or is it related to loyalty between agents on the negotiated submarket where the prices are not displayed and agents are not fully informed about the market situation.

To understand this dissimilarity between the submarket, we first dig in the quantities per couples each day then we look at the loyalty between agents using the probability of return to same agent. Hence two behaviours can be noticed for a buyer : being loyal or not being loyal to a seller.

Couples loyalty vs quantities

It is convenient to study the share of each submarket in the quantities exchanged each day between the couples. We denote :

- $\bar{q}_{ij\tau}^{neg}$ as the average of the quantities exchanged on the negotiated submarket between the couple (i, j) every day over all the period where both submarkets coexist
- $\bar{q}_{ij\tau}^{auct}$ as the average of the quantities exchanged on the auction submarket between the couple (i, j) each day over all the period where both submarkets coexist
- $\bar{q}_{ij\tau}$ as the average of the quantities exchanged on the both submarkets between the

couple (i, j) each day over all the period where both submarkets coexist

We calculate :

$$\bar{Q}^{auc}_{ij\tau} = \frac{\bar{q}^{auct}_{ij\tau}}{\bar{q}_{ij\tau}} \tag{B.8}$$

Figure B.16 represents the distribution of $Q^{auc}_{b_i,s_j,\tau}$ (Equation B.8) of the share of the auction market for the quantity exchanged. 49,5% of the quantity are sold on the auction market (Table B.8).

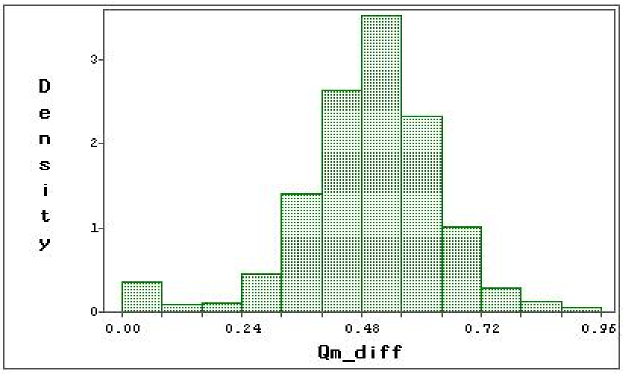


FIGURE B.16 – Distibution of the share of the average quantity

N	539
Mean	0.495
Variance	0.022
Skewness	-0.8073
Kurtosis	2.35

TABLE B.8 – descriptive statistics

We remark that there are no significant correlation between our $\bar{Q}^{auc}_{ij\tau}$ and Ml^{auct}_{τ} and between $\bar{Q}^{neg}_{ij\tau}$ and Ml^{neg}_{τ} as shown in Table B.9.

	$\bar{Q}^{auct}_{ij\tau}$		$\bar{Q}^{neg}_{ij\tau}$
Ml^{auct}_{τ}	-0.0973	Ml^{neg}_{τ}	0.0942
Prob > |r|	0.0238	Prob > |r|	0.0288

Table B.9 – Spearman Correlation

C Survival Appendices

C.1 Dendrogram of buyers according to quantities

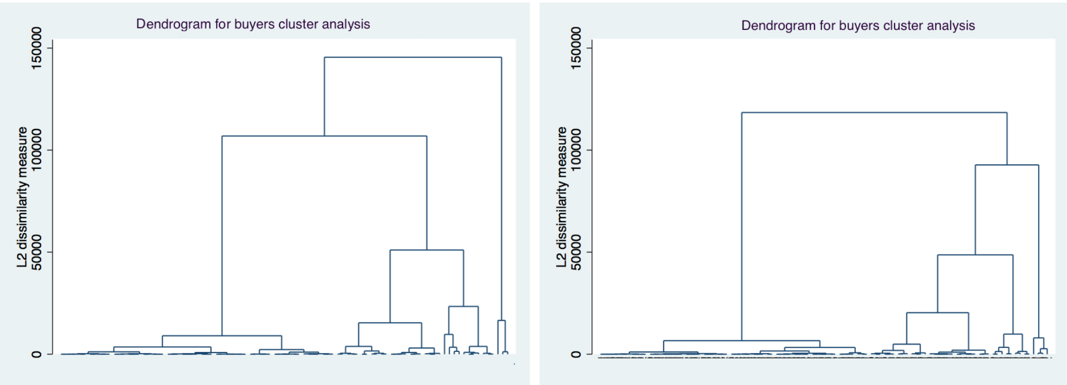


FIGURE C.1 – Dendrogram for buyers according to quantities exchanged on the negotiated (left) and auction (right) submarket

Variable Negotiated	Obs	Mean	Std.Dev	Min	Max
Small	57	470.16	318.73	31.85	1172.25
Medium	33	5051.72	3815.71	1571.70	18899.4
Big	3	31552.57	7369.63	26708.55	40033.70

TABLE C.1 – Clustering of buyers according to the quantity bought on the negotiated submarket

Dendrograms assure that buyers can be divided into three categories : The big ones, medium and the small ones. Their is no significant different between the buyers size among submarkets. What we meant is that a big (medium or small) buyer on an auction submarket is a big (medium or small) one at the negotiated one. All buyers transact with the same quantities (size) on both submarkets. But only 10% of the buyers do not have the same size among submarkets. These 10% are small buyers on one submarkets and medium one on the other.

Variable auction	Obs	Mean	Std.Dev	Min	Max
Small	60	315.45	249.67	8.833	1089.89
Medium	36	3883.56	2599.65	1304.79	10189.29
Big	4	19537.38	3111.84	15136.30	22439.87

TABLE C.2 – Clustering of buyers according to the quantity bought on the auction submarket

C.2 The buyers' characteristics according to size

The buyers characteristics according to size : quantity, species, degree and week. In this appendix, a characterisation for the buyers according to their size is done. As previously mentioned, buyers are divided into three categories : the small one, the medium and the big buyers. We should not mixed these categories with the segmentation done in the chapter considering the number of weeks spent on each submarket.

Auction submarket :

Figure C.2 represents 4 scatter plots specified to the buyers size on the auction submarket. The first one explains what "buyers size" means.

The small buyers exchange 900 kilos per week maximum. Medium buyers buy less than 15 000 kilos per week and the big ones (few ones) purchase more than kilos per week. The

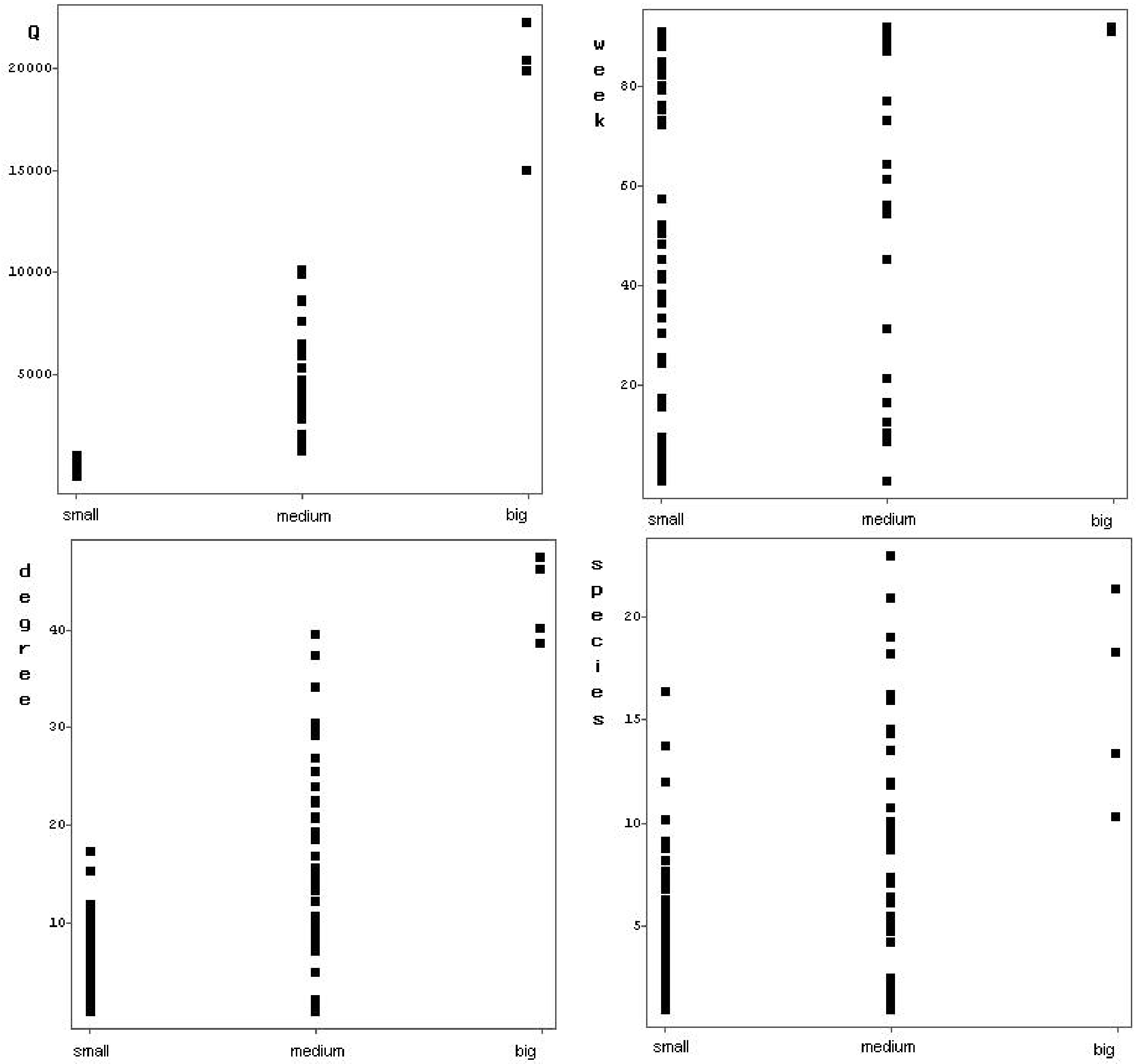


FIGURE C.2 – The scatter plot for the number according the the size of the buyer on the auction submarket

"week" scatter plot tells a lot. Big buyers are present weekly on the auction submarket. When it comes to small and medium buyers, we can say that buyers are heterogenous. There are "small" and "medium" buyers who came frequently to auction submarket : what explains the second category in the survival model : "the buyers who are indifferent among structures".

As for the third scatter plot, "the degree" represents the number of connected seller per buyer in average weekly [1]. Small buyers are connected to maximum 20 sellers per week. The number of connected sellers for medium buyers can go up to 40. This is not the case for big buyers on the auction submarket : the number of connected sellers is higher than 35 buyers. To note that these results are not seen in the duration analysis. So, why this difference ? Because the category which prefers to auction contains mainly big buyers (the big three ones). The other buyers who explain this category are the small and the medium ones. Therefore this high number for the degree is not seen in the chapter. The same explanation goes for the rest of this analysis.

Because buyers are heterogenous, the number of distinct species bought per buyer in average each week is not perfectly related to its size. The fourth scatter plots pictures this. "Big buyers" purchase at leat 10 different kinds of fish per week, as for the "small buyers" and "medium buyers" the interval is different : between 1 and 16 different types for small ones and between 1 and 23 for the medium ones.
The same analysis goes for the buyers on the negotiated submarket.

Negotiated submarket :

Figure C.3 represents the same 4 scatter plots according to the buyers size on the negotiated submarket. The first one explains also what "buyers size" means.

"Small buyers" on the negotiated submarket are the one who purchased less than 1500 kilos per weeks. Between 1500 and 19 000 kilos are bought by the medium ones. The "big ones" exchanged between 26 000 and 40 000 kilos. There are only three of them, what explains also the results that we had in the survival model. All of the three "big buyer" came frequently on the negotiated submarket. The "small buyers" are more heterogeneous.

1. To every buyer, we computed the average of the number of connected sellers per week

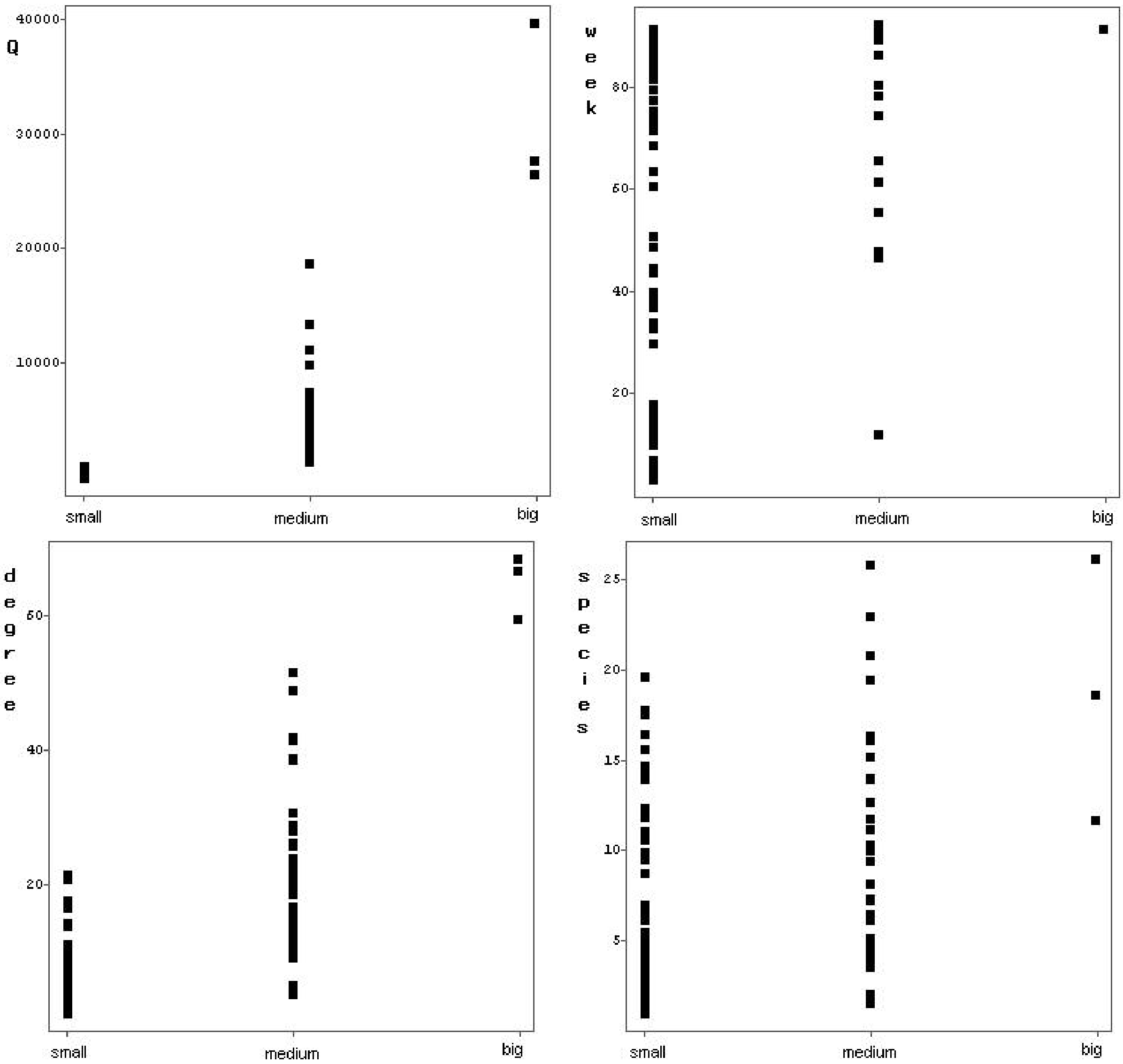


FIGURE C.3 – The scatter plot for the number according the the size of the buyer on the negotiated submarket

There exists buyers who came weekly and others who came just few times (4 times per example). This is not the case for the medium ones. All of them came more than 48 weeks (expect one 12 weeks).

The degree and the species analysis are similar to the analysis done on the auction submarket.

C.3 The hazard curves

Appendix C.3 illustrates the hazard curves for the different categories of buyers. The bell shape in the hazard curve (the red one, the negotiated submarket figure 1 for buyers who prefer negotiated structure, reflect a higher rate of failure that can be explained by a higher number of trustee buyers. Figure 2 represents buyers who visit both submarket equally. As seen the hazard curves is higher most of the time on the negotiated submarket and the gap is intense around week 10, (that confirm the results obtained in section 4.2). The bell shape in figure 3 is related to one buyer on the auction market. The two curves are coincident ones. Hence no differences in buyers behaviour for those who prefer auction mechanism.

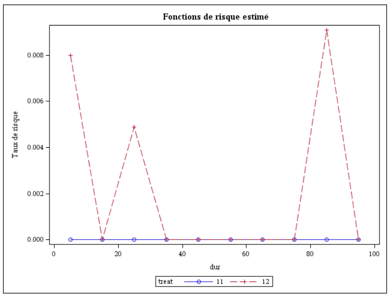


Figure 1

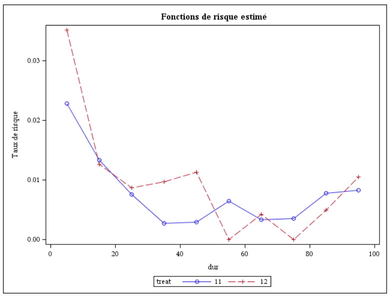


Figure 2

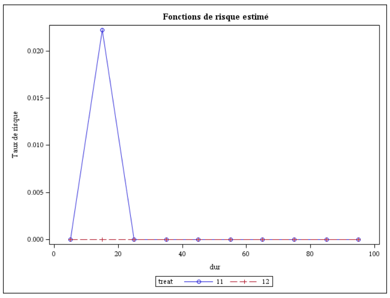


Figure 3

C.4 Probability of new encounters considering the past ones

In this appendix, we will explain the method of computing equation 3.6. It represents the probability that buyer i chooses seller j, with the same percentage (r) of transacted days a week t, given that i had already chosen j, r times a week $t-1$. For all the couples weekly formed on the auction and the negotiated submarkets, the upper probability is then calculated as follows :

$$Prob^{neg/auct}[(L_{ijt}^{r_t} = 1)|(L_{ijt-1}^{r_{t-1}} = 1)] = \frac{Prob^{neg/auct}[(L_{ijt-1}^{r_{t-1}} = 1) \cap (L_{ijt}^{r_t} = 1)]}{Prob(L_{ijt-1}^{r_{t-1}} = 1)} \tag{C.1}$$

$\forall$ $t > 0$, $\forall$ i $\in$ (1, 2, ..., N) and $\forall$ j $\in$ (1, 2, ..., M) .

with :

- $Prob^{auct}(L_{ijt}^{r_t} = 1)$ as the probability for a buyer i to transact with a seller j, r_t on the auction market
- $Prob^{neg}(L_{ijt}^{r_t} = 1)$ as the probability for a buyer i to transact with a seller j, r_t on the negotiated market
- $Prob^{auct}(L_{ijt-1}^{r_{t-1}} = 1)$ as the probability for a buyer i to transact with a seller j, r_{t-1} on the auction market
- $Prob^{neg}(L_{ijt-1}^{r_{t-1}} = 1)$ as the probability for a buyer i to transact with a seller j, r_{t-1} on the negotiated market

1. $Prob^{neg/auct}[(L_{ijt-1}^{r_{t-1}} = 1) \cap (L_{ijt}^{r_t} = 1)]$

   Each couple formed by a seller j and a buyer i is defined by its $value$. This $value$ is equal to 1 if the couple transacts week t and 0 if both of the buyer and the seller are present week t on the market (See figure C.4). Hence, the number of days that a couple transacts a week t is labeled by $encounter$ and is equal the the sum of $value$[2] and the number of the days couple (ij) is present on the market is equal to the number of 0 and 1 (the count command).

   Our r ratio used in the probability of return is represented in table C.4 by the $ratio\_week$ column.

$$ratio\_week = \frac{encounter}{presence} \tag{C.2}$$

2. Sum of value per week and per couple

Now, for each ratio r used, we repeat the following calculation.

We define $value\_t$ as the value that takes 1 if the couple meets more than x time per week and 0 if not. Hence, if $value\_t$ if the value at the period t , we define $value\_t+1$ as the value for the period $t+1$.

For each couple (ij), we look at two consecutive periods and we define the column no_change is equal to 1 if both of $value\_t$ and $value\_t+1$ are equal to 1, otherwise no_change is equal to 0.
Hence, the

$$Prob^{neg/auct}[(L_{ijt-1}^{r_{t-1}}=1)\cap(L_{ijt}^{r_t}=1)]=\frac{\sum no\_change}{\text{Number of total weeks}} \tag{C.3}$$

Buyer	Seller	Value_t+1	value_t	Date	week	Year	value	encouter	presence	ratio_week	no_change
2	87	0	0	16/05/2066	20	2066	0	1	4	0,25	0
2	87	0	0	17/05/2066	20	2066	0	1	4	0,25	0
2	87	0	0	19/05/2066	20	2066	1	1	4	0,25	0
2	87	0	0	20/05/2066	20	2066	0	1	4	0,25	0
2	87	0	1	23/05/2066	21	2066	0	2	4	0,5	0
2	87	1	1	26/05/2066	21	2066	0	2	4	0,5	1
2	87	1	1	27/05/2066	21	2066	1	2	4	0,5	1
2	87	1	1	29/05/2066	21	2066	1	2	4	0,5	1
2	87	1	1	30/05/2066	22	2066	1	2	6	0,33333333	1
2	87	1	1	31/05/2066	22	2066	0	2	6	0,33333333	1
2	87	1	1	01/06/2066	22	2066	0	2	6	0,33333333	1
2	87	1	1	02/06/2066	22	2066	0	2	6	0,33333333	1
2	87	1	1	03/06/2066	22	2066	0	2	6	0,33333333	1
2	87	1	1	05/06/2066	22	2066	1	2	6	0,33333333	1
2	87	1	1	06/06/2066	23	2066	0	3	6	0,5	1
2	87	1	1	07/06/2066	23	2066	1	3	6	0,5	1
2	87	1	1	08/06/2066	23	2066	0	3	6	0,5	1
2	87	1	1	09/06/2066	23	2066	1	3	6	0,5	1
2	87	1	1	10/06/2066	23	2066	1	3	6	0,5	1
2	87	1	1	12/06/2066	23	2066	0	3	6	0,5	1
2	87	1	0	14/06/2066	24	2066	0	0	3	0	0
2	87	0	0	15/06/2066	24	2066	0	0	3	0	0
2	87	0	0	17/06/2066	24	2066	0	0	3	0	0
2	87	0	0	20/06/2066	25	2066	0	1	6	0,16666667	0
2	87	0	0	21/06/2066	25	2066	1	1	6	0,16666667	0
2	87	0	0	22/06/2066	25	2066	0	1	6	0,16666667	0
2	87	0	0	23/06/2066	25	2066	0	1	6	0,16666667	0
2	87	0	0	24/06/2066	25	2066	0	1	6	0,16666667	0
2	87	0	0	26/06/2066	25	2066	0	1	6	0,16666667	0

FIGURE C.4 – Return probability example

2. $Prob(L^{r_{t-1}}_{ijt-1} = 1)$:

   The $Prob(L^{r_{t-1}}_{ijt-1} = 1)$ is equal to : The number of week a couple transact more than r time per week over the number of total weeks.

Bibliographie

Abbas, N. H. (2014), *The impact of trust relationships on environmental management in North Lebanon*, Universiteit Twente.

Abolafia, M. (1997), *Making Markets : Opportunism and Restraint Wall Street.*

Akerlof, G. (1970), 'The market for "lemons" : Quality uncertainty and the market mechanism', *The Quarterly Journal of Economics* **84**(3), 488–500.

Alesina, A. & Ferrara, E. L. (2002), 'Who trusts others ?', *Journal of Public Economics* **85**(2), 207–234.

Algan, Y. & Cahuc, P. (2010), 'Inherited trust and growth', *The American Economic Review* **100**(5), 2060–2092.

Allison, P. (1995), *Survival Analysis Using SAS : A Practical Guide*, SAS Publishing, SAS Institute Inc., SAS Campus Drive, Cary, North Carolina 27513.

Aranki, T. & Macchiarelli, C. (2013), 'Employment duration and shifts into retirement in the eu', *LSE paper* **58**.

Arellano, M. (1989), Duration models.

Arthur, W. B. (2013), 'Complexity economics : a different framework for economic thought', *Complexity Economics, Oxford University Press (forthcoming)* .

Atmar, W. & Patterson, B. (1993), 'The measure of oder and disorder in the distribution of the frangmented habitat', *Oecologia* **96**, 373–382.

Bajari, P., McMillan, R. & Tadelis, S. (2009), 'Auctions versus negotiations in procurement : an empirical analysis', *Journal of Law, Economics, and Organization* **25**(2), 372–399.

Bala, V. & Goyal, S. (2000), 'A noncooperative model of network formation', *Econometrica* **68(5)**.

Bala, V. & Goyal, S. (1998), 'Learning from neighbours', *Review of Economic Studies* **65**, 595–621.

Barabasi, A.-L. & Bonabeau, E. (2003), 'Scale-free networks', *Scientific American* pp. 50–59.

Bascompte, J., Jordano, P., Melián, C. J. & Olesen, J. M. (2003), 'The nested assembly of plant–animal mutualistic networks', *Proceedings of the National Academy of Sciences* **100**(16), 9383–9387.

Bastolla, U., Fortuna, M. A., Pascual-Garcia, A., Ferrera, A., Luque, B. & Bascompte, J. (2009), 'The architecture of mutualistic networks minimizes competition and increases biodiversity', *Letters, Nature* **458**(07950), 1018–1021.

Berg, J., Dickhaut, J. & Mccabe, K. (1995), 'Trust, reciprocity and social history', *Games and Economic Behavior* **10**, 122–142.

Bernasconi, M. & Galizzi, M. (2010), 'Network formation in repeated interactions : experimental evidence on dynamic behavior', *Springer- Verlag* **9**, 193–228.

Beugelsdijk, S. & van Schaik, T. (2005), 'Social capital and growth in european regions : an empirical test', *European Journal of Political Economy* **21**, 301–324.

Bewley, T. (1995), 'A depressed labor market as explained by participants', *American Economic Review* **65**, 250–254.

Blau, P. (1964), *Exchange and Power in Social Life*, John Wiley.

Blouin, M. (2003), 'Equilibrium in a decentralized market with adverse selection', *Economic Theory* **22**, 245–262.

Blume, L. (2010), 'Robustness and fragility of the markets', *American Economic Association* .

Boccalettia, S., Latora, V., Morenod, Y., Chavez, M. & Hwang, D.-U. (2006), 'Complex networks : Structure and dynamics', *Physics Reports* **424**, 175–308.

Bonacich, P. (1987), 'Power and centrality : a family of measures.', *American Journal of Sociology* **92**, 1170–1182.

Bonnal, L. & Fougère, D. (1990), 'Les déterminants indivuduels de la durée du chômage', *Economie et Prevision* **5**(96), 45–82.

Borlandi, M. (2005), 'Dictionnaire de la pensée sociologique', *Quadrige* .

Bottazzi, G., Dosi, G. & Rebesco, I. (2005), 'Institutional architectures and behavioral ecologies in the dynamics of financial markets', *Journal of Mathematical Economics Special Issue on Evolutionary Finance* **Volume 41, Issues 1-2**, pp 197–228.

Bramoullè, Y. & Kranton, R. (2007), 'Public goods in network', *Journal of Economic Theory* **135**(478-494).

Brehm, J. & Rahn, W. (1997), 'Individual-level evidence for the causes and consequences of social capital', *American Journal of Political Science* **44**, 999–1023.

Bulow, J. & Klemperer, P. (1994), 'Rational frenzies and crashes.', *Journal of Political Economy* **102**.

Bulow, J. & Klemperer, P. (1996), 'Auctions versus negotiations', *The American Economic Review* **Vol. 86**, pp. 180–194.

Burgos, E., Ceva, H., Hernández, L. & Perazzo, R. (2009), 'Understanding and characterizing nestedness in mutualistic bipartite networks', *Computer Physics Communications* **180**(4), 532–535.

Burgos, E., Ceva, H., Hernández, L., Perazzo, R. P. J., Devoto, M. & Medan, D. (2008), 'Two classes of bipartite networks : Nested biological and social systems', *Physical review* **78**, 046113.

Burgos, E., Ceva, H., Perazzo, R. P., Devoto, M., Medan, D., Zimmermann, M. & Delbue, A. M. (2007), 'Why nestedness in mutualistic networks ?', *Journal of Theoretical Biology* **249**(307-313), 307–313.

Cabral, L. (2005), 'The economics of tust and reputation : A primer', *working paper, first draft* .

Calvo-Armengol, A. (2004), 'Job contact network', *Journal of Economic Theory* **115**, 191–206.

Calvo-Armengol, A. & Jackson, M. O. (2009), 'Like father, like son : Labor market networks and social mobility', *American Economic Journal : Microeconomics* **1**(1), 124–150.

Calvo-Armengol, A., Verdier, T. & Zenou, Y. (2007), 'Strong and weak ties in employment and crime', *Journal of Public Economics, Elsevier* **91**(1-2), 203–233.

Canto-Sperber, M. (1996), 'Dictionnaire d'éthique et de philosophie morale'.

Chong, E., Staropoli, C. & Yvrande-Billon, A. (2013), 'Enchères ou négociations dans les marchés publics : Une analyse empirique', *Revue d'économie industrielle* (1), 51–72.

Chong, E., Staropoli, C. & Yvrande-Billon, A. (2014), 'Auction versus negotiation in public procurement : Looking for empirical evidence', *The Manufacturing Markets, Legal, Political and Economic Dynamics* pp. 120–142.

Christakis, N. & Fowler, J. (2007), 'The spread of obesity in large social network over 32 years', *New England Journal of Medecine* **357**, 370–379.

Christakis, N. & Fowler, J. (2008), 'The collective dynamics of smoking in a large social network', *New England Journal of Medecine* **358**(21), 2249–2258.

Coleman, J. (1990), *Foundations of Social Theory*, The Belknap Press of Harvard University Press.

Corominas-Bosch, M. (2004), 'Bargaining in a network of buyers and sellers', *Journal of Economic Theory* **1**, 35–77.

Corso, G., de Araujo, L. & de Almeida, A. (2011), 'Connectivity and nestedness in bipartite networks from community ecology', *Journal of Physics, IOP Science* **285**.

den Berg, G. V. (2000), 'Duration models : Specification, identification, and multiple durations', *MPRA : Munich Personal RePEc Archive* **5**(9446).

der Leij, M. V. & Goyal, S. (2011), 'Strong ties in a small world', *Review of Network Economics* **10**(2), 1–22.

Dincer, O. & Uslaner, E. (2007), 'Trust and growth', *Nota di Lavoro, Fondazione Eni Enrico Mattei* **73**.

Dutta, B. & Jackson, M. O. (2000), 'The stabilbity and efficiency of directed communications networks', *Review of Economic Design* **5**, 251–272.

Dutta, B. & Mutuswami, S. (1997), 'Stable networks', *Journal of Economic Theory* **76**, 322–344.

Ermann, L. & Shepelyansky, D. (2013), 'Ecological analysis of world trade', *Physics Letters A* **377**(3-4), 250–256.

Fafchamps, M., Ductor, L., Goyal, S. & Leij, M. V. D. (2013), 'Social networks and research output', *Review of Economics and Statistics* .

Fehr, E. (2009), 'On the economics and biology of trust', *Journal of the European Economic Association* **7**(2-3), 235–236.

Fougère, D., Golfier, C., Horny, G. & Kremp, E. (2013), 'Quel a été l'impact de la crise de 2008 quel a été l'impact de la crise 2008 sur la défaillance des entreprises ?', *Economie et Statistque* **462-463**(69).

Fougère, D., Kamionka, T. & Prieto, A. (2010), 'L'efficacité des mesures d'accompagnement sur le retour à l'emploi', *Revue Economique* **61**(3), 599–612.

Fukuyama, F. (1995), 'Trust : The social virtues and the creation of prosperity', *New York : Free Press* .

Fulmer, A. & Gelfand, M. (2012), 'At what level (and in whom) we trust : Trust across multiple organizational levels', *Journal of Management* **38**, 1167–1230.

Gale, D. (1987), 'Limit theorems for markets with sequantial bargaining', *Journal of Economic Theory* **43**, 20–54.

Galeotti, A. & Goyal, S. (2010), 'The law of the few', *American Economic Review* **100(4)**, 1468–92.

Gallegati, M., Giulioni, G., Kirman, A. & Palestrini, A. (2011*a*), 'What's that got to do with the price of fish ? buyer's behavior on the ancona fish market.', *Journal of Economic Behavior and Organization* .

Gallegati, M., Giulioni, G., Kirman, A. & Palestrini, A. (2011*b*), 'What's that got to do with the price of fish ? buyers behavior on the ancona fish market', *Journal of Economic Behavior &amp ; Organization* **80**(1), 20–33.

Glaeser, E., Laibson, D., Scheinkman, J. & Soutter, C. (2000), 'Measuring trust', *The Quarterly Journal of Economics* **115**(3), 811–846.

Glaeser, E., Sacerdote, B. & Scheinkman, J. (1996), 'Crime and social interactions', *The Quarterly Journal of Economics* **111**(2), 507–548.

Gode, D. K. & Sunder, S. (1997), 'What makes markets allocationally efficient ?', *The Quarterly Journal of Economics* **112(2)**, pp 603–630.

Goldberg, V. P. (1977), 'Competitive bidding and the production of precontract information', *The Bell Journal of Economics* pp. 250–261.

Goyal, S. (2009), *Connections : An Introduction to the Economics of Networks*, Prince.

Goyal, S. & Vega-Redondo, F. (2000), *Learning, network formation and coordination*, Mimeo.

Graddy, K. & Hall, G. (2011), 'A dynamic model of price discrimination and inventory management at the fulton fish market', *Journal of Economic Behavior &amp ; Organization* **80**(1), 6–19.

Granovetter, M. (1973), 'The strenght of weak ties', *American journal of sociology* **76**, 1360–1380.

Granovetter, M. (1985), 'Economic action and social structure : The problem of embeddedness', *American Journal of Sociology* **91**.

Grossman, S. & Stiglitz, J. (1976), 'Information and competitive price systems', *American Economic Review* **66**(2), 246–253.

Guiso, L., Sapienza, P. & Zingales, L. (2008), 'Trusting the stock market', *The Journal of Finance* **LXIII**(6), 2557–2599.

Guiso, L., Sapienza, P. & Zingales, L. (2009), 'Cultural biases in economic exchange ?', *The Quarterly Journal of Economics* **124**(3), 1095–1131.

Hansen, M. (1999), 'The search-transfer problem : The role of weak ties in sharing knowledge across organization subunits.', *Administrative Science Quarterly* **44**, 82–111.

Harari-Kermadec, H. (2008-2009), Econométrie 2 : Données en strates et modèles de durée. INSEE S. Lollivier.

Hausmann, R. & Hidalgo, C. A. (2014), *The atlas of economic complexity : Mapping paths to prosperity*, MIT Press.

Helliwell, J. (1996), 'Economic growth and social capital in asia', *NBER Working Paper No.* **5470**.

Hendricks, K., Piccione, M. & Tan, G. (1995), 'The economics of hubs : the case of monopoly', *Review of Economic Studies* **62**, 83–99.

Holm, H. & Danielson, A. (2005), 'Tropic trust versus nordic trust : experimental evidence from tanzania and sweden', *The Economic Journal* **115**, 505–532.

Jackson, M. O. (2007), 'The study of social networks in economics'.

Jackson, M. O. (2008), *Social and Economic Networks*, Princeton University Press.

Jackson, M. O. (2009), 'Networks and economic behavior', *Annual Review of Economics* **1**, 489–513.

Jackson, M. O. & Watts, A. (2002), 'The evolution of social and economic networks', *Games and Economic Behavior* **41**(2), 265–291.

Jackson, M. O. & Wolinsky, A. (1996), 'A strategic model of social and economic networks', *Journal of Economic Theory* **71**(1), 44–74, reprinted in Networks and Groups : Models of Strategic Formation, edited by Dutta and Jackson, Springer–Verlag, Heidelberg 2003.

Karpik, L. (1989), 'Economie de la qualité', *French Review of Sociology* **30**(2), 187–210.

Kiefer, N. (1988), 'Economic duration data and hazard functions', *Journal of Economic Literature* **26**(2), 646–679.

Kirman, A. (2010), *Complex economics : individual and collective rationality*, Routledge.

Kirman, A. & Moulet, S. (2008), 'Impact de l'organisation du marché : Comparaison de la négociation de gré à gré et des enchères descendantes', *Document de travail, GREQAM, Marseille* .

Kirman, A., Moulet, S. & Schulz, R. (2008), 'Price discrimination and customer behaviour : empirical evidence from marseille', *GREQAM document de travail* **57**.

Kirman, A. P. (1997), The economy as an interactive system, *in* 'Santa Fe Institute Stidues in the Science of Complexity-Proceedings', Vol. 27, Addison-Wesley Publishing CO, pp. 491–532.

Kirman, A. P. & Vriend, N. J. (2001), 'Evolving market structure : An ace model of price dispersion and loyalty', *Journal of Economic Dynamics and Control* **25**, 459–502.

Kirman, A., Schulz, R., Hardle, W. & Werwatz, A. (2005), 'Transactions that did not happen and their influence on prices', *Journal of Economic Behavior & Organization* **56**(4), 567–591.

Kirman, A. & Vignes, A. (1990), *Price Dispersion : Theoretical Coordination and Empirical Evidence from the Marseilles Fish Market*, Macmillan.

Kleinbaum, D. G. & Klein, M. (2012), *Survival Analysis : A Self-Learning Text*, Vol. XV, third edition edn, Springer.

Kramer, R. (1999), 'Trust and distrust in organizations : Emerging perspectives, enduring questions', *Annual Review of Psychology* **50**(1), 569–598.

Kranton, R. & Minehart, D. (2000), 'Networks versus vertical integration', *Rand Journal of Economics* **31**(3), 715–753.

Kranton, R. & Minehart, D. (2001), 'A theory of buyer-seller networks', *American. Economic Review* **91**(3), 485–508.

Kuhn, J. (2005), 'On today's business ethics', *EPIC New York, Columbia University* .

Ladyman, J., Lambert, J. & Wiesner, K. (2013), 'What is a complex system ?', *European Journal for Philosophy of Science* **3**(1), 33–67.

Lermercier, C. (2005), 'Analyse des réseaux et histoire', *Revue d'histoire moderne er contemporaine* **2**, 88–112.

Lillard, L. (1993), 'Simultaneous equations for hazards : Marriage duration and fertility timing', *Journal of Econometrics* **56**, 189–217.

Manelli, A. M. & Vincent, D. R. (1995), 'Optimal procurement mechanisms', *Econometrica : Journal of the Econometric Society* pp. 591–620.

Mansur, E. & White, M. (2007), 'Market organisation and efficiency in electricity markets', *Working Paper* .

Maskin, E. S. & Riley, J. G. (1985), 'Auction theory and private value', *The American Economic Review* **75**(2), 150–155.

Mccabe, K. A., Rigdon, M. L. & Smith, V. L. (2007), 'Sustaining cooperation in trust games', *Economic Journal* .

Medan, D., Perazzo, R. P., Devoto, M., Burgos, E., Zimmermannd, M. G., Cevac, H. & Delbuee, A. M. (2007), 'Analysis and assembling of network structure in mutualistic systems', *Journal of Theoretical Biology* **246**, 510–521.

Meidinger, C., Robin, S. & Ruffieux, B. (1999), 'Confiance, réciprocité and cheap talk', *Revue Economique* **50**, 5–44.

Memmott, J., Waser, N. M. & Price, M. V. (2004), 'Tolerance of pollination networks to species extinctions', *Proceedings of the Royal Society of London B : Biological Sciences* **271**(1557), 2605–2611.

Mignot, S. (2012), *Negocier ou enchérir : l'influence des mécanismes de vente. Le cas du marché de Boulogne-sur-Mer*, Université Paris 2- Assas.

Mignot, S., Tedeschi, G. & Vignes, A. (2012), 'An agent based model of switching : The case of boulogne s/mer fish market', *Journal of Artificial Societies and Social Simulation* .

Milgrom, P. (1986), *Advances in Economic theory :fifth world congress of the Econometric Society*, Cambridge University Press, London : Mac Millan and Co, chapter Auction Theory, pp. 11 – 32.

Milgrom, P. (2004), *Putting auction theory to work.*, Cambridge.

Milgrom, P. R., North, D. C. & R.Weingast, B. (1990), 'The role of institutions in the revival of trade : the law merchant, private judges, and the champagne fairs.', *Economics and Politics* **2**(1).

Molm, L., Schaefer, D. & Collett, J. (2009), 'Fragile and resilient trust : Risk and uncertainty in negotiated and reciprocal exchange', *Sociological Theory* **27**(1), 1–32.

Montgomery, J. (1991), 'Social networks and labo-market outcomes : Towards an economic analysis', *The American Economic Review* **81**(5), 1408–1418.

Moreno, D. & Wooders, J. (2004), 'The efficiency of centralized and decentralized markets for lemons', *University of Arizona Department of Economics Working Paper* .

Moreno, D. & Wooders, J. (2010), 'Decentralized trade mitigates the lemons problem', *International Economic Review* **51(2)**, 383–399.

Myers, C. & Shultz, G. (1951), *The Dynamics of a Labor Market*, Prentice-Hall N.Y.

Myerson, R. (1977), 'Graphs and cooperation in games', *Mathematics of Operations Research* **2**(3), 225–229.

Nahapiet, J. & Ghoshal, S. (1998), 'Social capital, intelectual capital, and the organizational advantage', *The Academy of Management Review* **23**(2), 242.

Newman, M. J. (2003), 'The structure and function of complex networks', *SIAM Review* **45**, 167–256.

North, D. C. (1990), *Institutions, Institutional Change and Economic Performance*, Cambridge Univesity Press, the Press Syndicate.

Onnela, J., Saramaki, J., Hyvonen, J., Szabo, G., Lazer, D., Kasbi, K., Kertesz, J. & Barabasi, A. (2007), 'Structure and ties strenghts in mobile communication networks', *Proceedings of the National Academy of Sciences* **104**, 7332–7336.

Orléans, A. (2000), 'La théorie economique de la confiance et des limites', *Cahiers de Socio-Economie* pp. 59–77.

Patterson, B. & Atmar, W. (1995), 'The nestedness temperature calculator', *AICS Research Inc., University Park, NM and the Field Museum, Chicago, IL.* .

Paxton, P. (1999), 'Is social capital declining in the united states ? a multiple indicator assessment', *American Journal of Sociology* **105**, 88–127.

Plickert, G., Wellman, B. & Côté, R. (2007), 'It's not who you know, it's how you know them : Who exchanges what with whom ?', *Science Direct Social Networks* **29**, 405–429.

Putnam, R. (1993), 'Making democracy work', *Princeton University Press.* .

Rees, A. & Shultz, G. (1970), 'Workers in an urban labor market', *University of Chicago Press* .

Rosenberg, M. (1956), 'Misanthropy and political ideology', *American Sociological Review* **21**, 690–5.

Roth, A. E. (2002), 'The economist as engineer : Game theory, experimentation, and computation as tools for design economics', *Econometrica* **70**(4), 1341–1378.

Rubinstein, A. & Wolinsky, A. (1985), 'Equilibrium in markets with sequantial bargaining', *Econometrica* **53**(5), 1133–1150.

Sapio, S., Kirman, A. & Dosi, G. (2011), The emergence and impact of market institutions : The wolesale market for fish and other perishable commodities, Technical report, LEM Working Paper Series.

Seligman, A. (1998), 'The problem of trust', *Acta sociologica* **41**(2).

Smith, V. L. (1962), 'An experimental study of competitive market behavior', *Journal of Political Economy* **70**(2), 111–137.

Smith, V. L. (1964), 'Effect of organization on competitive equilibrium', *Quarterly Journal of Economics* **78**(94), 181–201.

Sztompka, P. (1999), *Trust : A sociological Theory*, Cambridge : Cambridge University Press.

Uslaner, E. & Brown, M. (2005), 'Inequality, trust and civic engagement', *American Politics Research vol. 33 no. 6* **33**(6), 868–894.

Verboven, F. (2008), *Price Discrimination (Empiracal Studies)*, S.N. Durlauf and L.E. Blume (eds).

Vignes, A. & Etienne, J.-M. (2008), 'What influences the price formation on an exchange market ? the case of the marseille fish market', *Journal of Economic Behavior and Organization* .

Vignes, A. & Etienne, J.-M. (2011), 'Price formation on the marseille fish market : Evidence from a network analysis', *Journal of Economic Behaviour and Organization* **80**.

Watts, D. J. & Strogatz, S. H. (1998), 'Collective dynamics of 'small-world' networks', *Letters to Nature* **393**, 440–442.

Weisbuch, G., Kirman, A. & Herreiner, D. (2000), 'Market organisation and trading relationships', *The Economic Journal* **110**, 411–436.

Wiggins, S. N. & Lane, W. T. (1983), 'Quality uncertainty, search, and advertising', *The American Economic Review* **73**(5), 881–894.

Wolinsky, A. (1990), 'Information revelation in a market with pairwise meetings', *Econometrica* **58**, 1–23.

Yamagishi, T. (2001), *Trust as a form of social intelligence. In Trust in Society*, KS Cook.

Zak, P. & Knack, S. (2001), 'Trust and growth', *The Economic Journal* **111**(470), 295–321.

Résumé :
La définition et la mesure de la confiance restent toujours une ambiguité en économie, sociologie et philosophie. Les "trois papiers" de cette thèse comparent, tout en considérant le niveau de confiance deux mécanismes de vente : la vente de gré à gré et la vente aux enchères. Le marché de Boulogne-sur-Mer, caractérisé par la coexistence stable de deux systèmes de vente constitue le centre de notre analyse empirique. Ces trois papiers sont précédés par une introduction générale et une revue de la littérature. Le premier papier est dédié à la comparaison des deux structures en termes de robustesse et de "nestedness", en s'appuyant sur de outils de réseaux employés par les écologistes. Le deuxième papier analyse la création des liens de confiance du côté de l'acheteur à l'aide d'un modèle de durée. La taille des acheteurs a son rôle sur la confiance. Le troisième papier s'intéresse à l'effet de l'indice de confiance sur les "outcomes" des transactions. Des graphes bipartis et homogènes montrent une différence de structure. Nos résultats affirment que le marché de gré à gré est plus atteint par la confiance comme l'information est décentralisée. Les agents se basent sur cette confiance comme alternative au risque. Cela n'est pas le cas des enchères où l'information est connue.

Title and Abstract :
How to define and measure trust is still an enigma in economics, philosophy and sociology. This "three papers" thesis compares two different mechanisms - negotiated (decentralised) and auction (centralised) - on the basis of trust. Through an empirical study, the level of trust is evaluated and its impact is analysed on the "Boulogne-sur-Mer" fish market characterised by a stable coexistence of these two mechanisms. The three papers are preceded by a general introduction and a literature review. Paper one aims at comparing the nestedness and the robustness of both submarkets. Social network tools of ecologists are applied in order to provide an answer. Paper two models trust creation on both structures from the buyer side using the survival analysis and considering the buyer size. Paper three studies the effect of a trust index on the outcomes of transactions. Bipartite and projected graphs reveal the difference between submarkets. This thesis shows that the negotiated market is marked by a higher level of trust as agents interact and are not fully informed about the market situation unlike the auction one where information is centralised. We believe that trust is a way out of risk when there is lack of information.