Trust Somebody but Choose Carefully: an Empirical Analysis of Social Relationships on an Exchange Market

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Abstract. This article analyses the influence of trust on the functioning of a market for perishable goods, where there exists no quality signal and quantities can be scarce. On this market, agents can choose between bidding or exchanging through bilateral transactions. Starting from the empirical analysis of a market with a peculiar organization we propose a measurement of trust, based on the dynamics of agents' encounters. We then analyze the differences in the social network structures and estimate how they affects the market outcomes. 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 depends on something more. Clearly, the prices of the bilateral transactions are the consequences of economics and non economics determinants. At first glance, the stable co-existence of two market structures looks like a paradox. Our results help to understand the distinctive characteristics and functioning of each sub-market.

Introduction

A fundamental assumption in economics is that rational individuals act in their own self interest. One implication is that, when trading, buyers are supposed to seek for the lowest price and sellers for the highest one and social interactions are not considered. In line with that, the literature has accepted for a long time the idea that centralized markets, with common information and no friction, are more efficient. Nevertheless, some recent results weaken this idea of centralized market dominance. Moreno & Wooders (2010) show that decentralized organization allows both high and low quality units trade. Moreover, when frictions are small, the surplus realized is greater than the competitive surplus. Moreno & Wooders (2016) studies non stationary dynamic decentralized markets with adverse selection. They show that when the horizon is finite, the surplus in the equilibrium exceeds the competitive surplus. It is now largely accepted that social relationships affect the efficiency of a market structure (centralized or decentralized) (Babus et al. 2013, Opp & Glode 2016, Glode & Opp 2017).

If it is easy to understand how trust can influence pairwise exchanges, the way it may affect a centralized market remains unclear. The literature is quite sparse on this subject. In a context where investors have knowledge about trustees before transactions occur and where trustees compete with each other for access to investors, natural selection can favor both trust and trustworthiness, even when individuals interact through an anonymous prices mechanism. (Manapat et al. (2012)).

In the present article, we postulate that bilateral trust between individuals comes from repeated social relationships. In the line of Hernández et al. (2018), 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 have with other traders: the more two persons exchange together, the higher the level of trust. We then assume that these bilateral social relationships affect the way people exchange together. This assumption implies that we consider a market where multiple couples of traders interact, as a social network.

Following this train of though, we build a specific social network, based on trust relationships. We first associate a trust index to each couple of agents (a buyer and a seller). We then consider that two traders trust each other when their trust index is high (belonging to the top 10% of the trust index distribution). From these sub-set of trust index, we create a network of trust relations. This procedure is done for both sub-markets.

This article is organized as follows: Section 1 outlines the main characteristics of the market and describes the database. Section 2 presents some descriptive statistics. The measure of trust is disclosed in Section 3 and Section 4 concerns the network analysis. The conclusion follows.

1 The main market features and the data

We present here some particular features of the Boulogne s/mer fish market, through the analysis of a detailed database, consisting of 300 000 daily transactions on the period 2006-2007.

The market: The Boulogne s/mer fish market is located in the North of France near Belgium. This market is a daily one, open 6 days a week. Agents are heterogeneous on both sides of the market. They are or sellers or buyers. Sellers are boats owners and their boats are of different capacities. 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 both sub-markets. Mignot et al. (2012) show the existence of two behaviors: 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. The prices of the transactions are known by everybody and then, constitute a public information signal. Each lot offered for sale is carefully described (type of fish

and quantities, name of the boat).
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, their ability to bargain and transact and the special links they can have with agents of the other type (buyers or sellers).

The data: 200 boats are registered in this market and designated as "sellers" in what follows. 100 buyers purchase regularly, most of them on both submarkets. 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. The analysis of the database tells a story of heterogeneity. First statistical results exhibit heterogeneous behaviors in terms of quality and quantities exchanged, on the both sides of the market. On the period studied, the two sub-markets (auctions and negotiated) are of equal importance (45% of volume for the auctions market, 55% for the bilateral one): the same agents transact on the two "sub-markets" and the same types of fish are sold through both mechanisms (80 different species of fish are traded). Between 37% and 54% of each of the four main fish species (in term of quantities) are sold on the auction market which suggests an equivalent distribution of the production between the two market mechanisms.

2 Stylized facts

2.1 Prices distributions

We compare now the distributions of transactions prices and the agents behavior on both sub-markets. In a first step, we compute the weekly aggregate prices per sub-market, using a classic Paasche index, which allows to take into account the heterogeneity of the goods:

$$\hat{P_w} = \sum_{i=1}^{i=N} (p_{i,w}(\frac{q_{i,w}}{\sum_{i=1}^{i=N}(q_{i,w})})) \tag{1}$$

$p_{i,w}$ being the price per kilo of a transaction [1] in week w, $q_{i,w}$ the quantity sold in this transaction, and N the number of transactions made in week w.

The first observation we can make from Tab.1 is that the prices are higher on the negotiated market (average and median) and that the prices distributions behave differently on the two markets. The very high kurtosis value on the bilateral market suggests a leptokurtic distribution, with fat tails: the "rare

[1] In this article, unless stated otherwise, all the prices considered will be prices per kilo.

Price	Auction	Pairwise
Average	2.38	2.94
Median	2.31	2.71
Skewness	0.87	3.00
Kurtosis	1.71	16.74
Std dev	0.51	0.82

Table 1. *Descriptive statistics describing the weekly aggregate prices distributions on the two sub-markets. Both standard-deviation and average prices have significant differences. Observe a leptokurtic distribution of pairwise prices.*

events", *i.e.*, very low or high prices (outliers), are quite frequent. The higher standard-deviation confirms a higher uncertainty on the bilateral market. Finally we observe that both distribution have a positive skewness, which is way higher for the pairwise distribution. A positive skewness is associated to asymmetry : the mass of the distribution is concentrated on the left, where the values are lower, with a fat tail on the right. The "rare events" correspond to high prices. The auction distribution, even if not following a normal law, is less asymmetric than the pairwise one (skewness of 0.87 vs. 3.00 and kurtosis of 1.71 vs. 16.74 on the bilateral market) and then exhibits relatively few high values. Clearly, pairwise exchanges are more risky and this result is in line with the literature.

2.2 Buyers' and sellers' pairing

We start by checking pairing strategies of buyers and sellers on both submarkets, looking a the distributions of the number of buyers (respect. sellers) that each seller (respect. buyer) transact with on the whole period considered For sellers the number of partners is not a strategic variable on auction as they can't directly act on it. When looking at the buyers strategy, we observe a propensity to exchange with a higher number of sellers on the negotiated market than on the auction one. We guess here that the trade network is more dense on the negotiated market that on the auction one.
In a second step, we seek to estimate the intensity of social links for the different agents. Equation 2 represents, for an agent i, the ratio α_i of the number of transactions carried out by a trader divided by the number of agents he traded with on the whole period. This ratio should give a first estimation of the intensity of links for each agent. A high value should indicate an agent involved in loyal relationships.

$$\alpha_i = \frac{number \ \ of \ \ transactions}{number \ \ of \ \ traders} \tag{2}$$

The aggregate descriptive statistics are summarized in Tab.2.

The mean and the median of α_i are higher on the bilateral market than on the auction one (for both buyers and sellers). For a given number of transactions,

α_i buyers side	Auction	Negotiated
Mean	13.51	19.63
Median	6.31	12.17
α_i sellers side	Auction	Negotiated
Mean	16.77	23.15
Median	4.77	19.61

Table 2. *Mean and Median for buyers and sellers ratio distributions on both markets.*

a buyer (respect. seller) trades with less sellers (respect. buyers) on the bilateral market than on the auction one. We observe a large difference between the mean and the median on the auction market and this can be due to a large number of people, coming rarely and buying at random. When looking at the data, we observe a high number of buyers coming rarely on auction market, while on the decentralized market, traders are present more regularly.

These first results suggest that the bilateral market is more risky, and that on this sub-market traders seem to choose their partners more carefully. Empirical evidence suggests the existence of loyal behavior on the decentralized market, which could help to mitigate the risk.

3 A measure of trust

Let's do now the hypothesis that auctions do not facilitate loyal strategies, while on the bilateral market people can choose with whom they exchange. Once on the decentralized market, people can either exchange with someone they trust or exchange at random. Because people are not present every day, it can happen that a very loyal agent has no other choice than exchanging with a non-usual suspect.

Consider now a bilateral market, where there is no arbitrage, composed by N buyers i, and M sellers j, who buy and sell regularly during τ periods, τ=1...T. At each period τ, a buyer i and a seller j can both be present ($P_{i,j} = 1$) or not ($P_{i,j} = 0$). If both are present they can exchange ($L_{i,j} = 1$) or not ($L_{i,j} = 0$).

3.1 Looking for a signal of trust

We now measure trust by the intensity of the matching. Do buyers and sellers match at random, following the opportunity of common presence or do they strategically choose their partners ? We first look at the correlation between $M_{i,j}$ the number of days a couple (buyer i and seller j) is present on each sub-market, and $B_{i,j}$ the number of encounters. We compute $M_{i,j} = \sum_{\tau=1}^{T} P_{i,j,\tau}$ and $B_{i,j} = \sum_{\tau=1}^{T} L_{i,j,\tau}$.

Looking at the correlation between $B_{i,j}$ and $M_{i,j}$, we observe a stronger correlation between these two values when exchanges are centralized. The value is higher on the auction market than on the bilateral one (0.77 vs 0.58). The linear regression of $B_{i,j}$ on $M_{i,j}$ (Table 3) shows that the R^2 of the linear fit is at 0.60 for the auction versus 0.35 for the decentralized market.

	auction	negotiated
R^2	0.60	0.35
Coef	0.32	0.16
std dev	0.002	0.002
Pr $>$ t	$<$0.0001	$<$0.0001
Correlation	0.77	0.58

Table 3. *Strength of the relation between $B_{i,j}$ and $M_{i,j}$ on the negotiated and the auction market.*

On the auction market, the only fact of being both present can explain most of the exchanges. When it comes to pairwise exchanges, the only fact of being present at the same time do not imply common trades. We conclude that pairwise trading depends on something more than random meeting. Our hypothesis is that exchanges on the bilateral market are conditioned to loyal relationships and trust behaviors.

We now do the assumption that the more people exchange together, the more they trust each other. It allows to define a trust index $R_{i,j}$ (Eq. 3) for each possible couple i, j by a ratio of the total number of common encounters on the sum of the total encounters for i and the total encounters for j.

$$R_{i,j} = \frac{2 * B_{i,j}}{S_i + S_j} \tag{3}$$

With $S_i = \sum_j B_{i,j}$ and $S_j = \sum_i B_{i,j}$

The trust index will take values comprised between 0 and 1, we will consider that the higher the value, the more they trust each other.
The question is to understand if the presence of trust and the differences in the trust distributions has an influence on the formation of prices on each market. The next step consists in exploring the influence of trust on the formation of prices, when transactions are pairwise and when the prices mechanism is an auction one.

3.2 Influence of the trust index on prices

Do personal links affect the trading outcome? The following GLM model (see equation 4), seeks to evaluate the influence of the trust index on the formation of transaction prices. Because of the heterogeneity of the variables, different dummies are included in the model. The explained variable is the log of the price of each transaction. Dummies allow to take into account the weekday ("weekday" variable), the month ("month") and the year ("year") effects, as well as the species ("Specie" variable) effect. The results are given in Table 4.

$$P_{i,j,\tau,t} = \beta_1 + \beta_2 \cdot R_{i,j} + \beta_3 \cdot Weekday_\tau + \beta_4 \cdot year_k + \beta_5 \cdot month_k + \beta_6 \cdot Specie_k + v_{i,j,\tau,t} \quad (4)$$

	Auction			Pairwise		
Price	Coef	Std Dev	Pr > t	Coef	Std Dev	Pr > t
Intercept	-0.07	0.12	0.56	0.73	0.08	<.0001
$R_{i,j}$	0.62	0.13	<0.0001	2.99	0.06	<.0001
R squared	0.73			0.78		
nb observations	201047			279219		

Table 4. *Log-level estimation results (Eq. 4) for both sub-markets.*

Trust index positively influences the price of transactions, and this influence is higher on the bilateral market than on the auctions. We obtain here two important results, which are that trust influences more the prices when transactions are bilateral and that this influence is positive. When a buyer trusts a seller, he/she agrees to pay a higher price.On a market with no quality signals and scarce resource, the risk (of getting no fish or getting fish of poor quality) is on the buyer side. Agreeing to pay a higher price to some particular sellers can be viewed as an insurance. The fact that trust has a higher influence when the price results from bilateral negotiation, implies that the influence of trust on the negotiated market can't be fully explained by a simple reputation effect, as same traders exchange on both sub markets.

4 Network analysis

4.1 Bipartite trust network

People are of different type (buyers or sellers) and a link exists when two agents of different types trust each other. We build for each sub-market a bipartite network formed of two types of nodes, buyers and sellers, on the total period. Two nodes of the same type cannot be linked.

Our definition of a link is based on the trust index (equation 3) as defined in Section 3. We then consider the entire distribution of trust index, including the null value (associated to couples with no trades). We have already explained that there is a possibility of random matching on this market. We assume now that trust indexes belonging to the $D9$ ninth decile of the total distribution of trust have a higher probability to result from strategical behaviors. In other words, we analyze the graph of the 10% strongest bilateral relations on each sub-market.

	Auction	Bilateral
Nodes	295	300
buyers	100	93
sellers	195	207
Links	1950	1925
Clustering(reinforcement)	0.71	0.39

Table 5. *Networks statistics.*

The descriptive statistics (see Table 5) display information.

Both sub-markets have a similar density equal to 0.1 because of the choice of the thresholds. The clustering coefficient we use here, as defined in Robins & Alexander (2004) is an indicator of inter-sellers and inter-buyers closeness. It measures the reinforcement between two individuals rather than the clustering of a group of individuals.

In other words, consider that two sellers S_i and S_j trust the same buyer B_k. The probability for S_j to trust a buyer B_l, $l \neq k$, is higher if S_i trusts B_l. We observe from Table 5 that this coefficient is higher on the auction market (71%) compared to the bilateral market (39%). This suggests a higher specialization on the auction market (specific groups of buyers regularly exchange with specific groups of sellers). When it comes to the bilateral market this phenomenon is really weaker (the clustering coefficient is much lower), each buyer trusts a specific group of sellers. Loyalty links seem based on something else than economic specialization.

4.2 The advantage of being central

We now attribute to each agent, a vector or trust indexes and a coefficient of centrality in the trust network. The centrality we use in this article is defined by the number of trust ties that a node has, divided by the maximum number of ties he could have.

To evaluate the influence of traders trust network on the market outcome, we analyze the effects of buyers' and sellers' centrality on prices. We use normalized degree centrality and measure its influence for both buyers and sellers (deg_i and deg_j).

$$P_{i,j,\tau,t} = \beta_1 + \beta_2 \cdot deg_i + \beta_3 \cdot deg_j + \beta_4 \cdot Species_t + \beta_5 \cdot Weekday_\tau + \beta_6 \cdot Month_\tau + v_{i,j,\tau,t} \tag{5}$$

As already done in Eq. 4, we control for the influence of the day of the week ($Weekday_\tau$), and the month ($month_\tau$). We also control for the global significance of the 80 species ($Species_t$) exchanged. The explained variable is the log of the price per kilo of a transaction t . Each transaction t involves a buyer i, a seller j and a specie on a given day τ.

The results are indicated in Table 6. The usual causalities (dummies variables as year, month or day...) are not displayed. We observe that the position of

	Auction			Pairwise		
Parameter	coefficients	Std err	$Pr > \|t\|$	coefficient	Std err	$Pr > \|t\|$
Intercept	0.03	0.12	0.76	0.87	0.08	<0.0001
centrality buyer	-0.41	0.01	<0.0001	-0.59	0.01	<0.0001
centrality seller	0.49	0.03	<0.0001	0.78	0.02	<0.0001
R squared	0.74			0.79		

Table 6. *Influence of centrality on prices for both sub-markets (log level estimation, Eq. 5).*

an agent has a significant influence on the transactions prices on both sub-markets, and that this influence is higher on the bilateral market (higher R squared and higher coefficients). This influence is positive for sellers and negative for buyers and this is in line with previous results on markets. On a market with frictions (search costs, private information), it is advantageous for a seller to establish links with a large number of potential buyers. On the auction market, the information is centralized and there is no search costs. Prices result from the competition between buyers. Partnerships cannot help.

On the buyers side, the coefficient is higher (in absolute value) on the pairwise market. More central buyers pay cheaper prices and this reflects a higher bargaining power (due to the higher number of potential sellers).

From these results, we can deduce two things. First that traders have an interest to establish as many trust links as they can. Second, it is clear that each trader has interest to build strong relationships with lonely traders. It seems that there is a competition among traders that trust a same partner.

4.3 Trust and centrality

We now want to introduce the $R_{i,j}$ term in the regression in order to control for the bilateral trust effect and isolate the influence of the position in the trust network. But an important question remains : what is the intensity of the correlation between traders trust indexes and their centralities? Do these two variables represent two different phenomenons ? To answer this question we measure the correlation between the trust index and traders centrality on each market (Tab.7).

	Auction	Pairwise
Correlation for sellers	0.62	0.26
Correlation for buyers	0.39	-0.19

Table 7. *Correlation between traders trust indexes and centralities.*

Concerning the auction market, we observe a high correlation between the bilateral trust index of traders, and their respective centralities. Without surprise, we can conclude that interlinks on auctions result from the competition mechanism, more than from trust strategies. This is in line with the results in Section 4.1, Table 5, that exhibits a high clustering on the centralized market.

Meanwhile, the correlations are weak on the pairwise market. Agents with high trust indexes are not always central agents. Being central or trusting partners correspond to two different strategies.

While the correlation is high between trust and centrality on the auction market, it seems that two different effects correspond to these two different variables on the pairwise market. In what follows, we measure (cf. Eq. 6) the respective effects of centrality and trust on the decentralized market.

$$P_{i,j,\tau,t} = \beta_1+\beta_2 \cdot R_{i,j}+\beta_3 \cdot deg_i+\beta_4 \cdot deg_j+\beta_5 \cdot Species_t+\beta_6 \cdot Weekday_\tau+\beta_7 \cdot month_\tau+v_{i,j,\tau,t} \tag{6}$$

The results are displayed in Table 8.

	Pairwise		
Parameter	coefficients	Std err	$Pr > \|t\|$
Intercept	0.82	0.08	<0.0001
centrality buyer	-0.56	0.01	<0.0001
centrality seller	0.67	0.02	<0.0001
$R_{i,j}$	1.34	0.07	<0.0001
R squared	0.79		

Table 8. *Influence of trust and centrality on prices (log level estimation, Eq. 6).*

As expected, introducing the trust index and centralities in the same regression decreases the influence of centralities on prices, and the influence of trust itself. But note that all coefficients stay significant. Even when adding the trust index in the regression, influence of centrality is far from being negligible. On the sellers side, it is clear that agents should better be central, with a high index of trust links. The effects of these two variables are positive and strongly significant. When coming to the buyers' side, the strategy of centrality seems to be more rational as it lowers the prices. But remember that bilateral trust increases prices, a buyer have to be cautious not being too dependent on some specific sellers. A buyer optimal strategy should result from a trade-off between being central to pay lower prices and investing in trust links to insure a stable level of quality of the good.

Conclusion

This article seeks to understand the influence of personal relationships on the outcome of a centralized market and a decentralized one. We use empirical measure of trust based on the intensity of relationships between people. The more people exchanges together, the higher their trust index We first establish that trust positively and strongly influences prices on both markets with a stronger causality when exchanges are pairwise. This stronger influence confirms that personal relations are more important on a pairwise market. This overprice associated to trust index can then be interpreted as an insurance cost, on a market with frictions costs, no quality signal and where the scarcity of the resource imply a risk for retailers. The fact that this influence is more important on the pairwise market compared to the auction one removes the possibility to explain completely this phenomenon by a reputation effect, traders being the same on both sub-markets.

We then measure the influence of centrality in these same networks. The position of an agent has a significant influence on the transactions prices on both sub-markets, and this influence is higher on the bilateral market. We associate a vector of trust values and a coefficient of centrality to each node (buyer or seller) of the network. An original result is that the level of correlation between these two values differs among the two markets. On the centralized auction market, trust corresponds to centrality. This result is not true anymore on the decentralized market. Trust index is not related to centrality but contribute to centrality to insure higher average prices to sellers involved in numerous trust relationships. A regressive estimation measures the respective influence of trust and centrality on the pairwise market outcome. If an optimal strategy for a seller is to be both central and with a high index of trust, a buyer will have to resolve a trade-off between being central (which lower the price) and being faithful, which increases the prices. Again, we believe that on a market with friction, no information signals and scarce resource, linking can help to minimize the risk. Being central shall help buyers to minimize the overprice of trust strategy. For a fish retailer, being central is clearly an advantage, allowing to obtain goods at a lower price. Having strong trust bounds with specific sellers can serve as an insurance against the risk of lacking supplies of a satisfying level of quality. An optimal strategy to ensure both supply and reasonable prices would be to create trust links with non central sellers to avoid competition. On the Boulogne s/mer fish market, it is a good strategy to trust some partners but important to choose them carefully. The stable co-existence of these two sub-markets where the same types of goods are traded by the same agents can seem paradoxical. Our analysis of the trust relationships help to resolve this paradox. The auction mechanism is an efficient one when people have no time for linking. They then trust the competitive market mechanism to insure an efficient redistribution of resources. But when they have time for linking, or exchanges involve rare goods, trusting some few partners can be optimal and the pairwise market mechanism allows this.

Bibliography

Babus, A., Kondor, P. et al. (2013), 'Trading and information diffusion in over-the-counter markets', *Manuscript (R&R Econometrica), London School of Economics* .

Glode, V. & Opp, C. (2017), 'Over-the-counter vs. limit-order markets: The role of traders' expertise', *Available at SSRN: https://ssrn.com/abstract=2697281* .

Hernández, L., Vignes, A. & Saba, S. (2018), 'Trust or robustness? an ecological approach to the study of auction and bilateral markets', *PloS one* **13**(5), e0196206.

Manapat, M. L., Nowak, M. A. & Rand, D. G. (2012), 'Information, irrationality, and the evolution of trust', *Journal of Economic Behavior & Organization* .

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 15 (2) 3* **15 (2)**, 3.

Moreno, D. & Wooders, J. (2010), 'Decentralized trade mitigates the lemons problem', *International Economic Review* **51**(2), 383–399.

Moreno, D. & Wooders, J. (2016), 'Dynamic markets for lemons: Performance, liquidity, and policy intervention', *Theoretical Economics* **11**(2), 601–639.

Opp, C. & Glode, V. (2016), (de) centralizing trade, *in* '2016 Meeting Papers', number 1591, Society for Economic Dynamics.

Robins, G. & Alexander, M. (2004), 'Small worlds among interlocking directors: Network structure and distance in bipartite graphs', *Computational & Mathematical Organization Theory* **10**(1), 69–94.
URL: *http://dx.doi.org/10.1023/B:CMOT.0000032580.12184.c0*