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# Trust on one market, robustness on the other: understanding the coexistence of decentralized and centralized markets

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**Centralized markets are often considered as being more efficient than bilateral exchanges, based on the fact that information is uniformly spread among all the agents. However, the influence of trust on the outcome of decentralized markets has been underlined by many authors. We present an empirical study of the distinctive Boulogne-sur-Mer fish market (where both buyers and sellers can choose to trade by either bidding or bargaining), focused on the interactions among agents. The approach we adopt derives from the studies of mutualistic ecosystems, where the agents are of two different types (like in plants - pollinators networks) and the interactions only take place between agents of different kind, bringing naturally a benefit for both. In our context, where the two kinds of agents are buyers and sellers, our study shows that their interactions, not only bring the economic benefits for the directly involved agents, but they also contribute to the stability of the market. Our results help to understand the surprising coexistence of the two forms of markets in the Boulogne sur Mer fish-market.**

social interactions | trust | mutualistic ecosystems | complex networks applications

## Introduction

**H**ow do social interactions influence the outcomes of the economic exchanges? While it is clear that human beings rely on cooperation with others for their survival [1], economic literature mainly supports the idea that auction markets, which imply a competition among buyers without direct social interactions with the sellers, are the most informational efficient way of organizing the exchanges. The information is the same for all the actors and there is no possibility of arbitrage [2]. Following on, a vast literature [3] has promoted the auction theory. More recent articles [4,5] underline that, when goods are heterogeneous and there exists no signal of quality, a decentralized mechanism (bilateral transactions) allows people to gather information and better evaluate the intrinsic quality of goods.

It is largely agreed that social networks underlie markets [6–8].

The stability of markets is essential to insure population welfare. This condition, (concerning the food markets) is one of the four pillars of food security [9]. Then, if networks underlie markets, their robustness should be studied as a necessary condition for markets stability. It is well known in network theory that the robustness of a network face to errors or attacks is strongly related to its topology, therefore we concentrate our study on the statistical properties of market’s interaction network.

Among other food markets, European fish markets are nowadays in a critical situation due to the scarcity of the resource which leads to fishing catch limits and quotas. The Boulogne-Sur-Mer Fish Market, the most important one in France in terms of quantity, is an excellent case study. This old daily market, which had operated historically in a decen-

tralized way, was led by EU regulations to adopt a centralized structure. This new way of functioning was firmly rejected by economic actors and, in 2006, it was finally admitted to allow the auction and bilateral negotiation sub-markets to co-exist in the same place. Every morning, when the buyers and the sellers (the fishermen’s boats) arrive on the market, they can choose to trade through an auction process or to exchange through pairwise transactions. In this paper we present a comparative data-based study centered on the interactions between actors, of both sub-markets. For several reasons, our dataset is ideal for our purposes. Detailed data concerning the daily transactions is available, allowing us to compare the behavior of actors in both sub-markets under similar economic, seasonal, climatic and social conditions, which reveals the importance of the social interactions on their economic strategies. The sample covers the period of reorganization, where the auction market split between a bilateral market and an auction one. We are then able to follow the different agents strategies: exploring the two sub-markets before adopting a strategy, preferring one of the two sub-markets or switching regularly.

The observed persistence of both sub-markets raises the question on the conditions of their stability. In other words, if the auction market is more efficient, why did it not outshine the bilateral one, leading to its extinction? One explanation could be related to the heterogeneity of the goods and a possible specialization of each sub-market (one selling the high quality/ high prices goods and the other specialized in low quality/low prices merchandise). However, this explanation does not seem to hold. In a previous article (cf. [10]), it has been shown that the probability of selling at a given price has a very similar distribution in both sub-markets. Around 80 different species are traded at Boulogne s/mer and all of them are sold on both markets. While some people (buyers or sellers) favor one market or the other, some others switch regularly, insuring that, in average, the same global quantities are sold on both markets (40% on the auction market, 60% on the bilateral one). In what follows, we investigate the role of agents’ behavior and their social concerns on the stability of this organization. In the auction mechanism, a neutral

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seller trades with buyers who compete against each other to get different units of a good. Decentralized exchanges, which allow pairs of non anonymous people to discuss and bargain before trading through frequent matching (as it is the case in a daily market), can easily bring out trust and loyalty behaviors. We explore through an empirical analysis the influence of trust and the emergence of loyal behaviors between buyers and sellers searching for stylized facts that might appear as characteristic of each sub-market.

Interactions among actors can be mapped on a *bipartite* complex network, where the nodes are of two different kinds (in this market, people are either buyers or sellers) and the links, that stand for the interactions, only connect nodes of different kinds.

Our data also allows us to build a network with *weighted links*, which describes the number of contacts of any pair of actors during the considered period, for each market. One originality of this study is to adopt an approach inspired from studies of *mutualistic* systems in Ecology to describe the differences in the market allocations coming from different prices mechanisms. A similar approach has been applied to the study import-export, and industrial ecosystems networks [11–14]. In mutualistic ecosystems like, plants-pollinators, or plants-seed dispersers networks, the interactions between two actors of different types bring a mutual benefit to both. The pattern of interactions observed in such systems is far from being random. Instead, it displays a particular structure called *nestedness*. This particular topology of the network is such that if the columns (rows) of the bipartite adjacency matrix are ordered in decreasing degree, then the rows (columns) appear to be ordered in the same way. So when species are ordered by decreasing degree, the contacts of a given species constitute a subset of the contacts of the preceding ones, thus leading to an adjacency matrix where all the contacts are located in a corner [15, 16] (see SI for details).

We investigate if a similar pattern, revealing some degree of organization (as opposed to a uniform distribution of contacts), is observed in either of the studied sub-markets.

A parsimonious analysis of networks’ properties shows that the structures of the social interactions involved in both sub-markets are different. In order to detect a signal of trust in our data, we define a *loyalty index* measuring the frequency of the interaction between the different couples of actors in both market organizations. The distribution of this loyalty index clearly depends on the type of sub-market; while it looks scale free in the decentralized (bilateral negotiation) sub-market, it shows a sharper decrease in the auction one, suggesting that for the latter, there is a characteristic value of loyalty such that the number of couples having a larger value decays very fast.

## Material and Methods

**Description of the data-set.** Since 2006, when the co-existence of both sub-markets started, an electronic detailed register of daily transactions on the Boulogne sur Mer Fish Market, is kept. For each transaction, the identification of the involved buyer and seller, the amount and quality of the exchanged goods and the price are registered. A seller  $i$  and the buyer  $j$  may hold several transactions in the same day (they may exchange different lots of fish at different prices). In this work, following [10] we coarse-grain daily transactions, and we consider that a seller  $i$  and a buyer  $j$  hold one *contact* in day  $d$  if they have performed *at least* one transaction that day regardless the price and the exchanged quantities. This simplifying hypothesis is based on previous results cited above,

which also show that, on average, prices are not significantly different on the two sub-markets. Hence in order to compare the individual behavior of actors in both sub-markets, we neglect the price discrimination as a first approximation.

**The model** From the previously described database, we build a network of interactions which can be coded into a *simple* bipartite matrix,  $K$ , whose elements  $K_{i,j} \in [0, 1]$  indicate if the seller  $i$  and the buyer  $j$  have interacted or not during the selected period, and the *weighted* bipartite matrix,  $B$ , of elements  $B_{i,j} \in \mathbb{N}$  which accounts for the number of contacts during the chosen period.

These matrices code a lot of information about the interactions among the agents of the market. The degree of an agent, measured in  $K$ , gives the number of *different* customers (providers) that a seller (buyer) has in the chosen period. The strength of an agent, measured in  $B$ , gives the total number of contacts that the agent has during the period, regardless the chosen counterparts. Comparing them, one can find out if the strength of a seller (buyer) comes mainly from contacts with different buyers (sellers) or from repeated contacts with some preferred group of buyers (sellers).

Nestedness is an indicator of some degree of structure in the network’s links, which is commonly observed in mutualistic ecosystems. It is opposed to a random uniform distribution of contacts and reflects a very particular organization. It highlights two different behaviors of the agents of each guild. Some of them are generalists, holding (many) contacts with counterparts of the other guild, while others are specialists, holding contacts mainly with generalist counterparts and rarely with specialists ones. Therefore, nestedness is not only different a random organization, it also differs from another common ordered state described by a block type matrix, which would indicate niche structure of the market.

The bipartite matrix of a perfectly nested network, when conveniently ordered in decreasing degree of one guild, shows a triangular shape, with all its zero and non zero elements on either side of a curve called *extinction curve* or *isocline of perfect nestedness* (IPN) that can be analytically determined as a function of the number of rows,  $n$ , and columns,  $m$ , and density of contacts,  $\phi$  [17] of the simple bipartite matrix (see SI for further details).

Several indicators aimed at quantifying nestedness coexist in the ecologic literature. They are based on different properties of a nested system, and have different advantages and drawbacks. In order to avoid bias, in this work we measure the nestedness of auction and negotiated sub-markets using four independent indices, each one targeting a different property of the nested matrix. We use the those indices proposed in the NED [18] package, plus an alternative measure of nestedness based on the resistance of the network to targeted attacks. If some species one guild are eliminated from the system, then the counterparts that remain without any contact will also disappear (secondary extinctions) and eventually the whole system may collapse. Robustness is the capacity of the system to resist to such attacks. The NIR, *Nesting index based on the robustness* of the network [19] exploits the fact that a nested system reacts very differently to attacks consisting in the suppression of nodes of one guild in increasing or decreasing degree order (see SI for more details).

An indication of trust may be obtained by measuring the frequency of contacts between any two agents. We define a *loyalty matrix* based on the weighted bipartite matrix  $B$ :

$$L_{i,j} = \frac{2 \times B_{ij}}{s_i + s_j} \quad [1]$$

where  $s_i = \sum_j B_{i,j}$  is the strength of agent  $i$ . Notice that  $L_{i,j} = 1$  if seller  $i$  and buyer  $j$  only transact among themselves and  $L_{i,j} \ll 1$  if seller  $i$  and buyer  $j$  transact much less between themselves than with others in the same period.

### Results

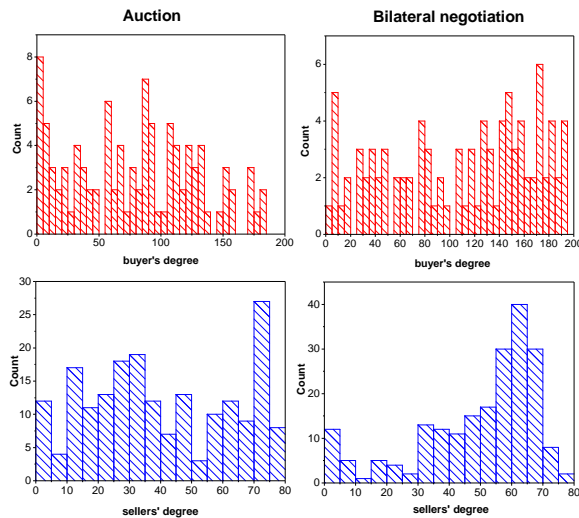
We have analyzed the properties of the *simple* bipartite matrix,  $K$ , and the *weighted* bipartite matrix,  $B$ , both in a global and in a detailed time scale, through the study of the networks obtained for both markets using not only the data integrated over all the considered period (18 months) but also discriminating it over the seasons and daily. This multiscale approach is useful because on one hand, data integrated over the whole period lead to matrices of larger size, allowing for the study of the statistical properties of the system and on the other, zooming into chosen periods (from seasonal to daily) gives information about the interaction's structure that could be washed out by the coarse-graining procedure.

Focusing on the structure of the interactions among agents brings valuable information about the agent's behaviour in each market.

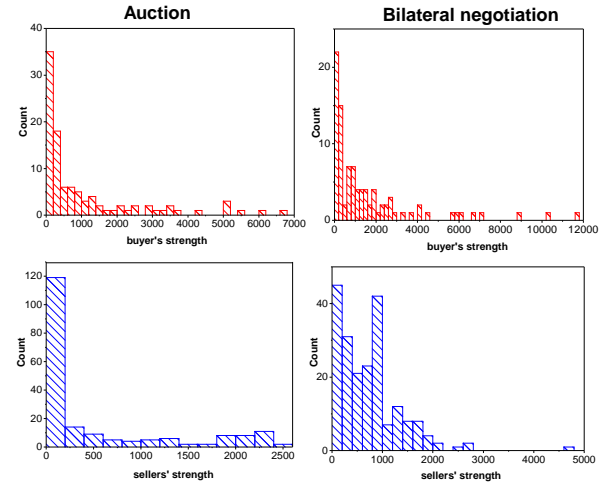
**Degree distributions: the number of partners.** The degree of a seller (buyer) gives the number of different customers (providers) the considered actor has, while the strength of a seller (buyer) measures the number of contacts that actor has held during the considered period (with the same or with different counterparts).

Fig. compares the degree distributions of buyers and sellers for the two sub-markets. The degree distribution for buyers (top) does not show any particular structure in any of the two sub-markets, looking like a uniform distribution with large fluctuations. However, high degrees are more frequent in the bilateral sub-market, which may be understood as a signature for the *exploration phase* of the buyers. When they enter this market they diversify the providers before choosing their preferred partners. This assumption will be comforted later by the comparison with the strength distribution.

Conversely, the sellers' degree distributions (bottom) of the two sub-markets are very different. The bilateral sub-market shows a left-skewed distribution, with a maximum around 60



**Fig. 1.** Degree distributions for both sub-markets (left auction, right bilateral negotiation). Top panels, buyers degree, bottom panels sellers' degree.

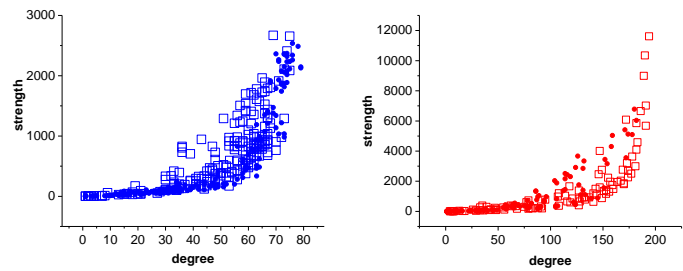


**Fig. 2.** Strength distributions for both sub-markets (left auction, right bilateral negotiation). Top panels, buyers degree, bottom panels sellers' degree. Bin size is the same (200) for all the panels.

customers, showing that about half of the sellers have many different customers, while for the auction market the distribution seems again, rather uniform with large fluctuations. This reflects the fact that, in the auction market sellers loose control of the transactions once the minimum price for their goods has been fixed, while, in the bilateral market, sellers can adapt their strategy to attract more customers.

**Strength distribution: the number of transactions.** In order to understand the following graphs, a rough estimation of the maximum number of transactions is helpful. In these markets there are typically 200 sellers and 100 buyers, and the full period covers 18 months, which is about 450 working days (the market does not function on Sundays). So a seller who is present all the market days and deals with all the buyers each day, will have at most a degree of  $k_s^{MAX} \approx 100$  and strength of  $s_s^{MAX} \approx 100 \times 450 = 45000$ . For a buyer in the same maximal conditions the degree will be of  $k_b^{MAX} \approx 200$  and the strength of  $s_b^{MAX} \approx 90000$ . The observed strength values are much lower because the actors are not present every day in the market, during the considered period.

Fig. shows that buyers' strength distribution are qualitatively similar for both sub-markets, except for the fact that the tails are much longer in the bilateral sub-market, show-



**Fig. 3.** Scatter plots of the strength vs. the degree correlation; open squares: bilateral sub-market market; full circles: auction sub-market. Upper panel: sellers, lower panel: buyers

ing the existence of some buyers that have carried out a large number of transactions during the whole period. Comparing with the values of the buyers’ degree distribution it appears clearly that those buyers have dealt repeatedly with the same sellers.

On the other hand, the comparison of sellers’ strength distributions of the two sub-markets is particularly interesting. While in the auction sub-market the distribution is uniform (except for peak at a very low number transactions), the bilateral sub-market distribution is Poisson-like, with an important fraction of sellers who manage to have many transactions during the period. The comparison with the values given by the degree distribution of sellers, reveals again that, in average, they must trade repeatedly with the same customers.

Fig. shows the scatter plots of the strength vs. the degree correlation in each sub-market. The sellers’ curve grows much faster in the bilateral sub-market than in the auction one, indicating that the sellers have loyal customers that come repeatedly to transact with them. The buyers’ curve is also interesting because it reveals there is an “exploratory” phase in the bilateral sub-market, where the buyers multiply the contacts with different providers (high degree and not so high strength) looking for those that are the most suitable for their needs.

**Loyalty index: a signature of trust** In order to understand the different results obtained for both sub-markets it is interesting to consider the intrinsic differences in the social relations among the economic actors in each of them. The loyalty matrix defined in eq. 1 is able to grasp these differences. While in the auction sub-market the buyer-seller interaction is mediated by the auctioneer, in the bilateral one, buyers can exchange directly with the sellers about the quality of the goods and the conditions of the exchange. Indeed, buyers seek for the trading conditions that suit them the most, through the experience they obtain after repeated exchanges.

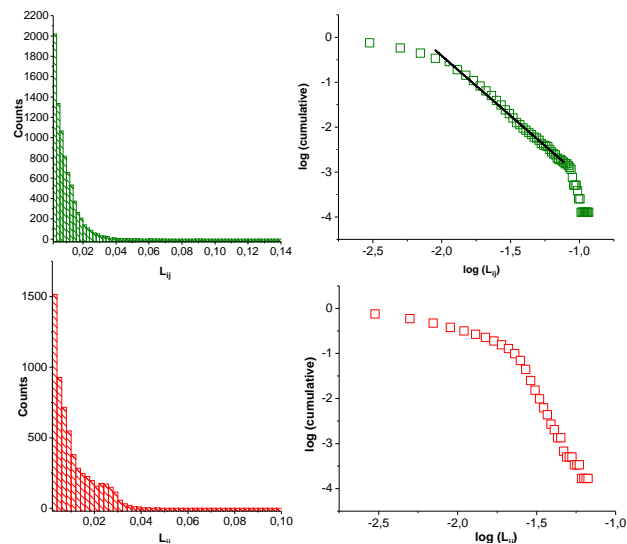
Fig. (left panels) shows the distribution of the loyalty for both markets. The negotiated market has both a larger tail and a larger number of couples with small loyalty index (50% over the auction market). These curves are measured over the whole period, so the excess of couples with small loyalty index in the negotiated market is again a signature of the “trials” done by buyers when they first join the market and the longer tail comes from the couples that establish as trading partners in the long run. These repeated interactions may also help the sellers to adapt their strategies.

Interestingly, the cumulative distributions of loyalty of these sub-markets (right panels) are qualitatively different. In the auction market, there are two different regimes: the number of couples having low and average loyalty values varies slowly until a critical value over which this number decreases very quickly. On the contrary for the bilateral market there is not such a characteristic critical value setting a change of regime. The cumulative distribution behaves as a power law distribution with a finite-size cutoff.

**The nested structure of bipartite matrices** Applying the tools developed to study mutualistic ecosystems, we investigate the structure of the interactions in both markets. The rationale behind this analysis is to search, in the most parsimonious way, for the traces of the actors’ behavior in these two different market frameworks.

In mutualistic ecosystems, the observed nested structure of the bipartite matrices describing the network, is known to contribute to their robustness and stability [20]. We have then analyzed the  $K$  matrices of both markets using different metrics developed for the study of ecosystems noting, however, that the densities of contacts of both markets measured over the whole period ( $\phi \approx 40 - 50\%$ ) are much higher than those typical of mutualist ecosystems, which are more than one order of magnitude lower. The results are displayed in Table 1, where for each index we compare with the nestedness value obtained for a set of random matrices of the same size and number of contacts.

All the indices (Table 1) show an important degree of nestedness in both sub-markets thus revealing the existence of generalist buyers and sellers along with some specialists of both guilds that mostly interact with generalists. This fact also excludes a *block type* adjacency matrix, which would have corresponded to a market segmented into “niches” of interaction among groups of buyers and sellers that only interact among themselves. Such a case would have led to very low values, in particular, of NODF index (see SI for details). Then, though the existence of some groups of specialized buyers and sellers cannot be excluded, they are not dominant in the structure of interaction of these markets.

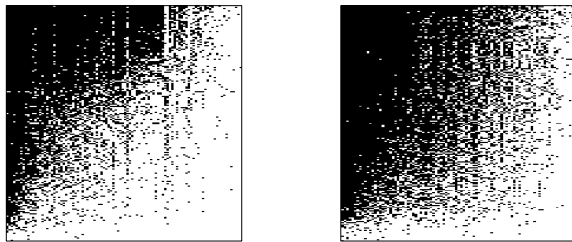


**Fig. 4.** Loyalty index, negotiated (auction) sub-market data is shown in upper (lower) panels. Left panels, loyalty distribution, right panels cumulative loyalty distribution.

**Table 1.** Nestedness measurement for both sub-markets, data corresponding to the whole period. Different indices have been used,  $N_s$ : number of sellers,  $N_b$ : number of buyers,  $\phi$  density of contacts. For each index  $X$ , the comparison with the average nestedness index calculates over 100 matrices of the same parameters is given, indicated as  $X(rand)$ . Recall that nestedness is important when  $T_{AP}$  and  $BRS$  are low and  $NODF$  is high compared to the corresponding random cases.

Sub-market	$N_s$	$N_b$	$\phi$	$T_{AP}$	$T_{AP}(rand)$	$NODF$	$NODF(rand)$	$BRS$	$BRS(rand)$
Auction	195	100	40.2	8.5	$85.13 \pm 0.69$	81.486	$40.62 \pm 0.25$	1336	$4381.16 \pm 23.016$
Bilateral	207	93	52.6	15.9	$84.662 \pm 0.69$	82.615	$52.451 \pm 0.295$	1636	$4493.54 \pm 25.324$

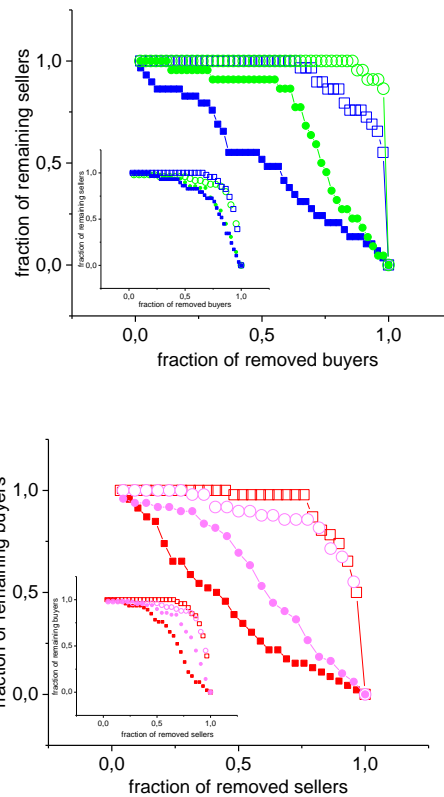
Fig. 5 shows the bipartite matrices  $K$  of both sub-markets for the whole studied period. They are ordered so as to put in evidence the nested structure (if any). Both guilds appear ordered by decreasing degree, with the maximum degree on the top-left corner. The resulting structure clearly shows that the interactions are not randomly distributed in a uniform way in any of these sub-markets.



**Fig. 5.** Bipartite interaction matrices ordered with the highest degrees of rows and columns on top and left respectively, Black dots correspond to  $K_{ij} = 1$ . Left panel: auction market, right panel: negotiated market.

We have also studied daily matrices using the nesting index based on robustness described in [19]. This index studies how the system resists to two extremes targeted attacks. In the attack strategy called *decreasing degree removal* (DDR) actors of one type (either buyers or sellers) are removed in order, starting from those of higher degree, and the actors of the other kind that are left without any contact are considered as having disappeared from the market (secondary extinctions). The Attack Tolerance Curve (ATC) gives the fraction of actors of one kind that remain in the market as a function of the fraction of removed actors of the other type. The extreme opposite attack strategy, called *increasing degree removal* (IDR), consists in the same procedure but now the actors to be removed are chosen in increasing degree order.

Fig. (upper panel) compares the fraction of sellers that remain in the market as buyers are removed applying both the DDR and IDR strategies. It can clearly be observed that



**Fig. 6.** Attack tolerance curves (ATC) for auction and negotiated markets, data corresponding to Friday, week 16, April, 2007 (Fridays are days of an important activity in the market). Upper panel: ATC for sellers. Open symbols correspond to the IDR strategy, and full symbols to the DDR strategy. Squares correspond to negotiated market data and circles to auction market data. Lower panel: ATC for buyers. Same symbols as in upper panel. In the insets the same curves with the same notation for the same system after 1000 randomization steps (ATCs for data corresponding to other Fridays of April of 2006 and 2007 can be found in SI). Color online.

for the DDR strategy, the ATC of the bilateral sub-market decreases faster than the ATC for the auction one, as buyers are removed. The area between the ATCs corresponding to the two attack strategies, which is proportional to the nesting index, is larger in the case of the bilateral sub-market (see SI for details).

The lower panel of Fig shows the ATC for buyers. Again we observe that the area between the curves corresponding to the two attack strategies is larger for the bilateral market, thus giving a larger nested index also for buyers in this market.

Interestingly, for the auction markets the ATC for sellers decreases very slowly even for the DDR strategy, indicating that an important fraction of the buyers should be removed before an important effect is observed for the sellers. Moreover, the DDR ATC curves for sellers, are step-wise while those for buyers are not (lower panel). This means that when high degree buyers are removed (absent from the market), most of the sellers may still find customers, while as sellers disappear, buyers are immediately affected. This effect is dominant in the auction sub-market, where a removal of about 50% of the buyers affects the sellers very little. This behavior reflects the different constraints for buyers and sellers in the market. While the former may change markets during one sales journey the latter must choose one market and stay there for the day. It is then easier for sellers to find customers (and so remain in the market) than the other way round.

As the density of contacts in these sub-markets is much higher than in mutualists ecosystems, the sensitivity of this nesting indicator is diminished. However it must be noticed that in all the cases the nesting coefficient (cf. the area among the IDR and DDR curves) is much larger than the one corresponding to randomized matrices (in the insets) of the same characteristics as the observed ones, thus indicating again that the structure of interactions is not random (see SI).

## Discussion

We have performed a data based study of the interaction networks of the two coexisting sub-markets (auction and bilateral negotiation) of the Boulogne-sur-Mer fish-market, searching for stylized facts on agent’s behavior and market structure. By applying tools issued from the study of mutualistic ecosystems, we observe that both submarkets are nested, though much denser than the ecologic systems. Moreover, we observe that the densities of contacts corresponding to the whole period and to daily data are quite different. While density is quite high for both markets when the whole period database is analyzed (50% for bilateral negotiation and 40% for auction), it is much lower, and with an inverted tendency, for daily matrices (10% and 20% respectively) thus affecting the nesting indices. In other words, at a daily level, the proportion of couples trading on the auction market is larger than in the bilateral negotiation one, and when data is integrated in the whole period, it is the negotiated market who has more trading couples. This can be understood recalling that the degree distribution of buyers in the negotiated sub-market shows a longer tail than in the auction one, revealing that a “searching phase” takes place in the former. This means that when buyers enter the bilateral sub-market, they first search for the

partners that suit them most, privileging interactions with them, afterwards. We also observe that the size of daily matrices is larger in the bilateral negotiation sub-market than in the auction one. So each day the affluence in the former is higher (the corresponding matrices are larger) but the number of trading couples trade is smaller (the corresponding matrices are sparser). From these observations, one can conclude that, in the bilateral negotiation sub-market, the trading couples are necessarily different from day to day so that, when superposing all the daily matrices in order to obtain the binary matrix of the whole period, its density of contacts appears to be larger.

The ATC curves show that the auction market is more robust. Almost 50% of the high degree buyers can be removed in daily matrices, without significantly affecting the fraction of sellers that will still hold at least one contact. For the negotiated market, removing the same fraction for buyers leaves a larger fraction of sellers without any contact. Certainly, this does not mean that removing those buyers is innocuous for the auction market, as this may affect the amounts exchanged or the prices. Instead, it reveals the importance of the social relationships between actors in the negotiated market. As sellers are fixed for the day, if the buyers that are loyal to them do not attend the market, those sellers do not find their counterparts.

The defined loyalty index measures the proportion of contacts between a given couple of agents with respect to the total amount of contacts of both, as an indicator of the trust existing inside that couple. Its cumulative distribution shows two regimes for the auction sub-market: for low values of loyalty, the cumulative distribution decreases slowly and a critical value of loyalty, beyond which it decreases very quickly, can be determined. On the contrary, the distribution of loyalty in the bilateral sub-market looks like a power law with no typical scale of loyalty.

**Conclusion** In spite of the widely accepted statement that auction markets are more efficient than bilateral negotiation ones, the case of Boulogne sur Mer Fish Market, where there is no signal of quality of the goods, shows that both market organizations coexist without one taking over the other. Our study provides a measurement of social interactions which enlightens, how they help to reinforce trust in the bilateral negotiation market, thus resulting in a mutual benefit for both, buyers and sellers, which compensates for the lack of information and the initial effort that is needed to build trust. It also shows empirical evidence supporting the efficiency of the auction market, which resists better to the extreme case of the absence of high degree buyers. Instead of one sub-market taking over the other, the advantages offered by each sub-market seem to increase the stability of the whole.

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# Trust on one market, robustness on the other: understanding the coexistence of decentralized and centralized markets

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## 1 SI Materials and Methods

### 1.1 Nestedness definition

Nested networks are commonly observed in Ecology, characterizing the interaction patterns of mutualist ecosystems like plant-pollinator or plant-seed dispersers networks. These networks have nodes of two different kinds (plants and animals) and the interactions take place only between nodes of different nature, leading to a bipartite adjacency matrix. This kind of interaction structure is also typical of markets, where the two kind of nodes are buyers and sellers and the interactions we are interested in (trading) only involve nodes of different kind.

A bipartite matrix is said to be nested if by ordering its columns (rows) in decreasing degree, rows (columns) become automatically ordered in the same way. Then, such matrix shows a triangular shape, with all its non zero elements on the same side (below or above depending in the labeling of axes) of a curve called *extinction curve* or *isocline of perfect nestedness* (IPN), that is schematically shown in Figure SI 1.

In this situation the counterparts of a column (row) element of degree  $k_1$  belong to a subset of the counterparts of a column (row) element of higher degree  $k_2 > k_1$ . This sequential inclusion of the contacts of the different actors like for the typical Russian "matryoshka" dolls, is at the origin of the name "nestedness".

This particular network order implies that the system is composed on one hand of generalists actors which diversify their counterparts, interacting most of the possible counterparts, and on the other, of specialist actors which preferably make contacts with generalists.

This pattern of connections is clearly not random, however it is not the only ordered pattern. An extreme opposite ordered pattern is the one given by a block matrix. The network is segmented in niches of interaction and it is not possible to find generalists.

### 1.2 Nesting measurements description

We briefly describe here the principal characteristics of the indices used in this work in order to quantify nestedness.

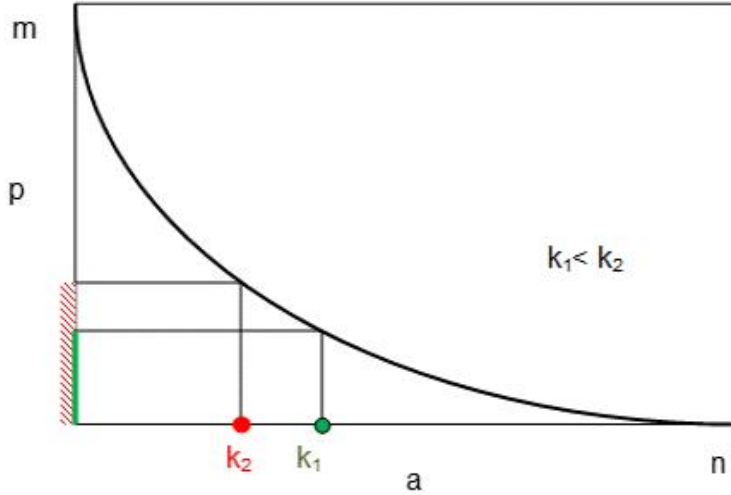


Figure 1: Schematic view of a perfectly nested bipartite matrix. The highest degree species are in the left down corner, such that all the contacts lie under the curve IPN. In this way the contacts of any species are a subset of the contacts of the preceding ones (see species of degrees  $k_1$  and  $k_2$ )

- ***The Atmar and Patterson Temperature,  $T_{AP}$***  [1]

Mapping the bipartite adjacency matrix into a continuous rectangle, the analytic expression of the IPN can be obtained in terms of two continuous variables  $a \in [0, n]$  and  $p \in [0, m]$  which constitute the continuous approximation to the discrete labels of the columns and rows of the adjacency matrix respectively. This approximation is expected to be correct in the limit of very large systems. Then, the non zero elements of the adjacency matrix correspond, in the rectangular surface of size  $m \times n$  to an area proportional to the density of contacts  $\phi = L/(m \times n)$ , where  $L$  is the total number of links. This area may be assumed to be colored and so the empty area represents the amount of zero elements of the adjacency matrix. The IPN is determined by  $m$ ,  $n$  and  $\phi$  [2].

Real systems, are not perfectly nested. The  $T_{AP}$  measures the distance, along the diagonal of the continuous approximation of the matrix, of the misplaced points (presence or absence of a contact over or under the IPN respectively). The  $T_{AP}$  will be large if there are several '1s' and zeroes on the wrong side of the IPN. It will be even larger if those misplaced points are located far from the IPN. So the lowest the measure of the  $T_{AP}$  of a given system the more nested it is.

The  $T_{AP}$  is known to have several drawbacks. The lack of normalization, its dependency on the density of contacts,  $\phi$ , and on the size and the eccentricity of the matrix, (how different  $m$  and  $n$  are), makes the comparison among different systems quite difficult. However it is largely used in order to compare the nestedness of an observed network with null models.

- ***The NODF index***, which stands for *Nestedness metrics based on overlap*

*and decreasing fills*, measures the average percentage of shared contacts of pairs of rows (columns) that have an ordered decreasing degree [3], leading to two values (one for rows and another for columns) which give an indication concerning the contribution of rows and columns to the observed ordered structure. This metrics measures the overlaps between all the possible pairs of rows (columns) only in the case where the pair is ordered in decreasing degree, otherwise it assigns a null value to the overlap. For these metrics the higher the NODF index the more nested is the system.

It is important to notice that NODF correctly assigns a very low nestedness value to modular networks (because, in general, elements within the same block have similar degree), but it may give a false negative (a low value) in the case of a nested network with multiple multiple rows (columns) with the same degree.

- **The BSD index**, (*Brualdi and Sanderson Discrepancy*), starts from a matrix in its maximum packing state, which corresponds to the best ordering of rows and columns compatible with the real contacts, and it measures the number of discrepancies (absences or presences) that should be 'corrected' in order to produce a perfectly nested matrix with the same parameters [4]. This index compares the real matrix with a perfectly nested one of the same parameters ( $n$ ,  $m$  and  $\phi$ ), however some ambiguity remains in the initial ordering when several possibilities exist (typically in the case of rows or columns with the same degree). As for the  $T_{AP}$ , the lower the value of the index the more ordered the system is.
- **The NIR, Nesting index based on the robustness**, introduced in [5], does not require the calculation of a theoretical IPN. It is based on the reaction of the network to *targeted* attacks. If some nodes of the same kind are eliminated from the network (primary extinctions), the nodes of the other kind that were connected with them, will loose links and may become disconnected from the network. In the ecological literature, it is said that the species represented by such nodes become extinct (secondary extinctions). As this process of removal goes on, the whole system may collapse. Robustness is the capacity of the system to resist to such attacks.

There are different ways of attacking a complex network, which are, in general, very robust face to random attacks. Two extreme strategies are considered to define the NIR. In the first one, the agents of one guild are removed *in decreasing degree order* (DDR), and in the second, they are removed *in increasing degree order* (IDR).

In ecological context the *Attack tolerance curve* (ATC) [6] [7] represents the fraction of species of one guild that survive, as species of the other guild are eliminated following a chosen strategy. In our context, the ATC gives the fraction of agents that remain in the market (they still find counterparts to deal with), as a function of the fraction of the removed counterparts.

The shape of the ATC depends on the chosen attack strategy. Moreover, for ecologic systems, which usually have a low density of contacts ( $\phi \ll 1$ ), the curvature of the ATC depends, for the (DDR) strategy, on the

degree of nestedness of the system: it is concave for nested systems and convex for random ones. Figure 2 shows the different typical behaviors of the ATC. Three different networks with the same parameters  $(n, m, \phi)$  are shown and for each one of the two extreme strategies considered, where open symbols correspond to IDR strategy and full symbols to the DDR one.

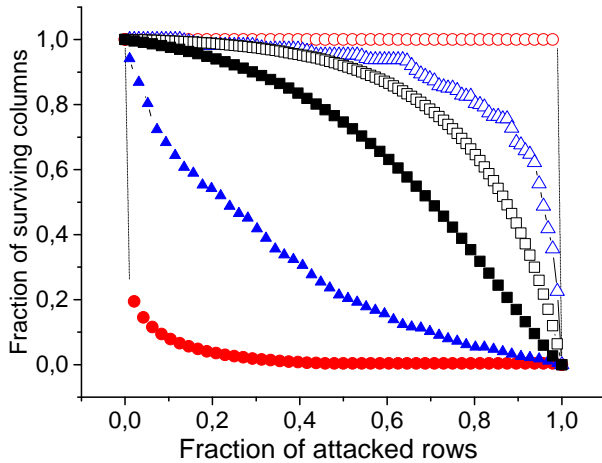


Figure 2: Attack Tolerance Curves for three different networks having the same parameters: triangles correspond to the real mutualist ecosystem of Clemens and Long [?], squares to a randomization of this system and circles to an artificial a perfectly nested network of the same size. Open and full circles correspond to the IDR and DDR attack strategies respectively.

The circles correspond to a perfectly ordered network, for IDR attack, as the row elements are removed starting for the one of lowest degree, the column elements remain unaltered until the last row element (the generalist) is removed. The area under this curve is  $R_{IDR} = 1$ , so a perfectly nested network is very robust face to this attack. For the DDR attack, a sudden collapse of the ATC is observed since the very first removal, because the first removed row element is the generalist. As the axis of the ATC gives the *fraction* of remaining and removed nodes, the area under this curve is  $R_{DDR} = \phi$ .

The open and full squares represent the ATCs corresponding to a random network with the same parameters, when the system is attacked with the IDR and the DDR strategies respectively, and the open and full triangles correspond to the same two attacks performed on a real network. The area between the ATCs corresponding to the two extreme attacks is maximum when the network is perfectly nested and minimum in the case where it is completely random. The real networks are never perfectly nested and the area between the two corresponding ATCs lies between these two extremes. The nesting coefficient can be defined as :

$$NIR = \frac{R_{IDR} - R_{DDR}}{1 - \phi} \quad (1)$$

where  $R_{IDR(DDR)}$  represents the area under the ATC corresponding to the performed attack. As NODF, this method also measures the contribution to nestedness separately for rows and columns. A global index is then obtained by the weighed mean of both contributions.

This method gives a correctly normalized index, with  $N=1$  for the perfectly nested network. Moreover it provides the ATCs corresponding to each attack strategy, which allows for a qualitative comparison of the robustness of the studied system with that of a randomized network of the same size.

However one must notice that this index loses sensitivity as the density of states approaches  $\phi \approx 50\%$ , for this reason is not a good indicator for the analysis of our data coarse grained over the whole period (see Table 1 in the article).

## 2 SI Results

Figures 3 and 4 show the ATCs for sellers and buyers for all the Fridays of April 2006 and 2007. They correspond to days of intense activity in the market, leading most of the time, to matrices of reasonable size. Table 1 shows the values of the parameters and the obtained nesting index for both markets for each day.

Year	Market	week	sellers	buyers	density (%)	<i>NIR</i>
2006	Bilateral	14	96	59	8.8	0.48
		15	55	50	11.6	0.48
		16	71	52	9.3	0.56
		17	70	55	11.8	0.57
	Auction	14	40	46	21.9	0.31
		15	14	40	20.3	0.56
		16	18	48	19.6	0.49
		17	14	44	29.3	0.36
2007	Bilateral	14	56	54	14.1	5.53
		15	53	51	10.1	0.47
		16	29	46	17.2	0.56
		17	59	52	11.6	0.51
	Auction	14	22	41	26	0.44
		15	55	55	16.1	0.51
		16	22	49	27.9	0.37
		17	42	50	15.2	0.4

Table 1: Network parameters and NIR index for daily data, corresponding to the four Fridays of April 2006 and 2007, for both sub-markets.

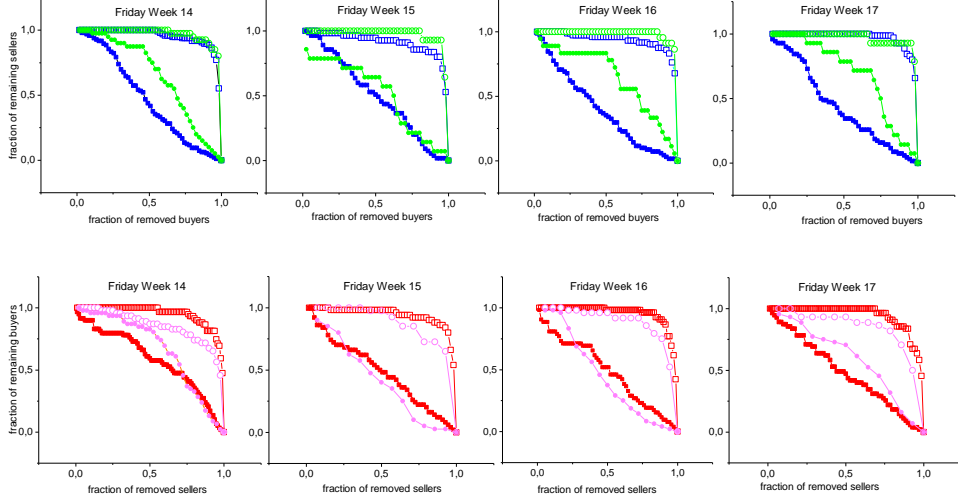


Figure 3: Attack tolerance curves (ATC) for market matrices corresponding to the four Fridays of April 2006. Upper panels ATC for sellers, lower panels ATC for buyers. Open symbols correspond to the IDR attack strategy, full symbols to the DDR attack strategy. Squares correspond to bilateral sub-market data, circles correspond to auction sub-market data. Color online

It is interesting to observe that though the matrices corresponding to the auction market are in general smaller than those corresponding to the bilateral one, they are also denser. So there are less actors but they trade more. This is consistent with the notion of efficiency associated to the auction market. As bilateral negotiations, take time, then the number of interactions is lower. A day by day comparison of the network of each market, indicates with the exception of week 15, where the  $NIR_{auct} > NIR_{bilat}$ , auction market, is in general, less nested than the bilateral one. We do not have a clear explanation for this phenomenon, and one must be prudent in the interpretation because daily matrices are smaller and then, statistically less significant, however we just notice that the Friday of week 15 was Easter Friday in 2006 and the first after Easter in 2007, which is a particular period for the fish demand in countries of christian tradition. More data would be needed to verify if this fact is related to the observed anomaly.

Interestingly, a comparison of the ATCs for sellers shows that only the curvatures corresponding to the auction market curves are always concave, is expected for the random networks, while bilateral market n curves have a convex or null concavity in general. This effect is less clear for buyers, reflecting the fact that sellers have an active role in the bilateral market, which is not present in the auction one.

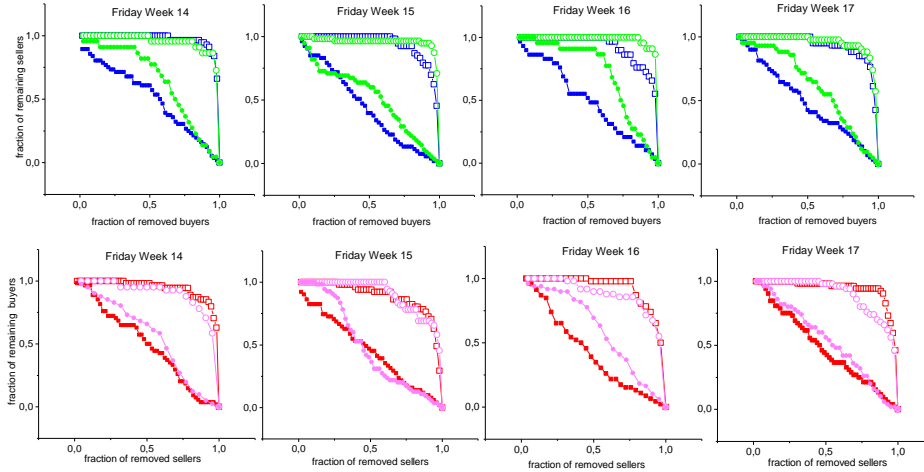


Figure 4: Attack tolerance curves (ATC) for market matrices corresponding to the four Fridays of April 2007. Upper panels ATC for sellers, lower panels ATC for buyers. Open symbols correspond to the IDR attack strategy, full symbols to the DDR attack strategy. Squares correspond to bilateral sub-market data, circles correspond to auction sub-market data. Color online

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