Journal of Economic Behavior & Organization 80 (2011) 50–67

Contents lists available at ScienceDirect

Journal of Economic Behavior & Organization

journal homepage: www.elsevier.com/locate/jebo

Price formation on the Marseille fish market: Evidence from a network analysis

Annick Vignes*, Jean-Michel Etienne

ERMES-CNRS, UMR 7181, Université Pantheon-Assas Paris II, 12, place du Pantheon, F-75230 Paris Cedex 05, France

ARTICLE INFO

Article history:
Received 6 August 2009
Received in revised form 7 July 2011
Accepted 9 July 2011
Available online 23 July 2011

JEL classification:
C01
D4
L14

Keywords:
Fish market
Price dispersion
Networks
Dynamic panel model

ABSTRACT

The empirical analysis of fish markets always reveals strong price dispersion for homogeneous or very similar goods. The problem is how to explain this price dispersion on a market where there is no evident arbitrage. Explanations proposed by different authors include differences in organization, the characteristics of the good, and the influences of social interactions between buyers and sellers. In line with the last of these three approaches, we consider the fish market of Marseille as a seller–seller network. We start by examining the influence of market interactions, through a static and then a dynamic econometric model. We then analyze the role of the seller's position in the network. We bring to light a surprising paradox, in that the sellers who share the most buyers with competitors (*i.e.* the most central sellers) charge the highest prices.

1. Introduction

For a long time, economic theory treated the market as a 'pure' economic relation, ignoring the specificity of individual behavior. Agents were usually considered to be anonymous and the influences of social interactions and social norms were ignored. Kranton and Minehart (2001) departed from this paradigm, building a model on the empirical premise that buyers and sellers need a link to exchange. This link can be of different types, essentially social or industrial.

Taking into account the way in which agents interact means recognizing that they are not anonymous. Brown et al. (2004) show experimentally that the absence of third party enforcement of contracts causes fundamental changes in the nature of market interactions. In certain situations, traders prefer to deal exclusively with the same partner, with the consequence that, over time, bilateral relationships come to dominate the market. The form and the influence of social interactions depend on the specificity of the goods and/or services supplied, on the organizational structures of the transactions and on the form of the links between agents. Jackson and Watts (2002) or Kosfeld (2004) show how an individual's payoff from an economic or social activity depends on the network of connections among individuals. As exhaustively summarized by Jackson (2008, 2010), the role of individual links and social networks has now been widely explored in the theoretical literature, as in the theory of international trade (e.g. Casella and Rauch, 2002; Rauch, 2001) or the analysis of non-competitive markets (e.g. Goyal and Joshi, 2003). Some authors have analyzed the process of exchanges in terms of a buyer–seller network rather than a market, following the path opened by Kranton and Minehart (2000, 2001). In these seminal articles, the authors seek

* Corresponding author. Tel.: +33 1 44 41 89 78.
E-mail address: AVignes@u-paris2.fr (A. Vignes).

0167-2681/$ – see front matter © 2011 Elsevier B.V. All rights reserved.
doi:10.1016/j.jebo.2011.07.003

to determine whether buyers and sellers, acting as non-cooperative maximizers, form a network structure that maximizes overall economic surplus. Studying the efficient link patterns, Kranton and Minehart (2001) observe that it is not necessary for all agents to be connected to all the others. Groups of people can be related by sparse links and this is not a sign of trading inefficiencies. It may represent an optimal trade-off between the cost of links and the potential gains from exchange. Jackson (2003) expands Kranton and Minehart's efficiency results, showing how over-connectedness can be avoided when the cost of a link is borne by both the buyer and the seller. Wang and Watts (2006) consider buyer–seller trade networks in a quality-differentiated product market, analyzing how the formation of links influences prices. In their model, heterogeneous sellers can join associations and buyers can establish links with these associations. In this particular theoretical framework, pairwise links between homogeneous buyers and heterogeneous sellers' associations can create trade frictions that result in inefficient outcomes.

In many applications, an individual's payoff depends not only on the value generated by the network but also on his position in the network. The link between power and centrality in exchange markets has long been explored by sociologists, but only more recently considered by economists. Cook et al. (1983) showed that power is not necessarily equal to centrality in exchange networks. The structure of the graph, especially in negatively connected networks,[1] plays a major role and experimental results are ambiguous. This result was undermined by Cook and Yamagishi (1992), who pointed out the role of mutual dependence in the formation of power. Corominas-Bosch (1999, 2004) studied how buyers and sellers bargain in an exogenously given network. The author explains how, when the realization of exchanges requires the existence of a social network, the network structure and the degree of competition in the market directly determine each individual player's bargaining power and the formation of prices. Conditions are established under which the subgame perfect equilibrium of the bargaining game is a situation where the short side of the market extracts all the surplus. Empirical evidence, as in Sorenson and Stuart (2001) or Hochberg and Ljungqvist (2007), testifies to the importance of an agent's position in the network, or more precisely the advantage of central positions. Analyzing the network of biotech firms, Powell et al. (2005) show the influence of different attachment strategies on the dynamics of investments.

The present paper proposes an empirical analysis of the role of pairwise individual links in the formation of transaction prices. We consider a homogeneous seller–seller network, where two sellers are linked when they share at least one buyer at a certain time. This network results from the projection of a buyer–seller network when both buyers and sellers are heterogeneous. Our field of application is the fish market of Marseilles. The fish market has a long tradition in the economic literature. This market represents a kind of economic paradox in the sense that, at first glance, one might conclude that it is a pure competitive market. And yet empirical analyses always reveal strong price dispersion for homogeneous or very similar goods. There have been a number of attempts to explain such a persistent result. Thornton (1869) sought to explain the discrepancy in terms of differences in trade mechanisms. For Pareto (1906), price dispersion is mainly explained by the fact that the good is perishable and cannot be stocked. Marshall (1930) notes that even in a market of very short period and with perishable goods, the cost of production has no perceptible influence on the day's bargaining. The quantity of the commodity, which cannot be stored, will be used as data by the dealers, and prices will be set so as to clear the market. Breaking with this literature, Graddy (1995, 2006) show that the Fulton fish market in New York is characterized by imperfect competition, demonstrated by the presence of price discrimination. In line with the approach pioneered by Thornton and Marshall, focusing on both the characteristics of the good and the organization of the market, Kirman and Vignes (1991) and Weisbuch et al. (2000) highlight the role of non-anonymity on daily markets. Because people know each other, they establish different strategies depending on the intrinsic characteristics of others.

Going a little further along the same path, our paper sets out to explain, through econometric and network analysis, why a decentralized market, where the main assumptions of pure competition are present and where there is no evident possibility of arbitrage, should exhibit a stable daily dispersion of prices for different units of a homogeneous good. We seek to determine whether this dispersion is due to pure market interactions (because people arrive on the market with individual reservation prices and adopt search processes shaped by their specific constraints) or to the existence of particular pairwise links. Our rich and detailed data set allows us to empirically verify some of the theoretical or experimental results quoted above. While most of the literature we have mentioned focuses on the exclusive influence of network connections in the exchange outcome, we particularly emphasize the significance of both market and non-market interactions in the formation of prices in an exchange market. The role of centrality in a homogeneous network is explored and our study gives evidence that here, a more central position ensures higher prices, as suggested by Corominas-Bosch (2004), Sorenson and Stuart (2001) or Hochberg and Ljungqvist (2007). But we also point out that sellers who are more central have a riskier position. The originality of our contribution then consists in considering a seller–seller network in which the most central agents are those who experience the highest level of competition. In this network, two agents are linked when they share the same buyers. Econometric estimations reveal firstly the fact that the price of one transaction is not entirely dependent on the prices and quantities of the other transactions, and secondly the importance of the agent's position in the network. An important result is that people who experience the higher level of competition are the ones who ask higher prices. In this market, for a buyer, being linked to a lot of different sellers has a cost: we obtain a result closed to those of Kranton and Minehart (2001) and Jackson (2003). Exploiting a sample of daily transactions, we demonstrate the stable co-existence of two

[1] A negatively connected network is, according to the authors, one where an exchange in one relation is contingent on non-exchange in another.

distinct behaviors: loyal and nomad. Our article reveals that the price of a transaction depends both on market interactions and on the seller's position in the network we have defined.

The next section outlines the functioning and particularities of the Marseilles fish market. Section 3 points out the influence of market interactions on the outcome of the exchanges. Section 4 describes the network analysis and the role of centrality in a seller–seller network. Section 5 concludes the article. Descriptive statistics concerning the database and detailed network statistics are given in Appendices A and B.

2. The main market features and the data

Saumaty (the Marseilles fish market) is a wholesale market. Deals are negotiated, and settled in a very short time. The prices are not posted. The bargaining process is something like a 'take it or leave it price'. There is no possibility of arbitrage. In 1987, it was one of the largest fish markets in the south of France, along with Sète (in the South-West). Both local catches and fish from the north of France are sold here. It is a market for professionals. The sellers are wholesale fish-merchants who buy their merchandise from local fishing boats and from outside fish-merchants: the buyers are essentially retailers, fishmongers, restaurant owners, and buyers for institutions (hospitals, company canteens, schools) and supermarkets. Buyers may come from very far away (the Alps, Vaucluse) or from Marseilles itself, meaning that some buyers have more time to search than the others (those who come from far away have to leave early to return to their businesses). Because this is a long-established and daily market, everybody knows each others' constraints. Fish is a perishable good. There is no possibility of storage, and all the merchandise exposed in the market at the beginning of the day (around 4 a.m.) must be sold before the market closes (around 8 a.m.). Once they have placed their orders, the sellers no longer have any control over the quantity they will have to sell. The only strategic variable is therefore the price. Obviously, each seller knows that the lower the price, the higher the demand. But he also knows that the demand for his fish strongly depends on the prices asked by the other sellers and the informal loyalty contracts that exist between particular sellers and buyers.

The data are encoded following a well-defined European classification taking into account the origin, and the main characteristics of the fish (size, weight, etc.). At first glance, the analyst could therefore consider different homogeneous goods, and ignore explanations in terms of vertical or horizontal differentiation. The database describes the daily transactions in the market of Marseilles. For each transaction, we know the date, the identities of the buyer and seller involved in the exchange, the species of fish, the quantity and the price. Because we want to work on a homogeneous good, we focus on the transactions of one common species, the sardine. Our sample covers transactions from January 1988 to December 1990, and more than 20,363 transactions concern sardines. On average, 42 sellers transact daily with some of the 929 registered buyers. The sellers are present six days a week, but most of the buyers come irregularly. 125 come regularly.[2] Over this period, around 16 tonnes of sardines were sold annually. The main descriptive statistics are given in Table A.4.

Fig. 1 shows the importance of each seller in terms of the number of buyers met (left-hand side) and quantities sold (right-hand side). The x-axis displays discrete values corresponding to the encoded identity of each seller (for example "30" corresponds to "Mr 30" who is selling about 17% of the total quantity to less than 10 buyers). It can be seen quite clearly that the sellers who sell the highest quantities are not exactly the ones who have the most customers.

Fig. 2 represents the prices and volumes of all the transactions for sardines made by the buyers during the three years studied. Although the macro behavior of the price–quantity relationship looks like the classic negative one, a lot of transactions do not seem to follow this rule. This can also be observed at a monthly level. Is this dispersion simply due to noise, or does the unit transaction price on this market depend on something more than the quantity exchanged?

The market studied presents several particularities, but two main stylized facts attract our attention: firstly, prices are not quoted and the dispersion of prices for homogeneous goods is quite wide. Secondly, people know each other and buyers can visit different sellers looking for prices below their reservation prices. Everybody can watch everybody else (particularly among the sellers) to get some idea of the level of prices fixed by the others: in this sense, each buyer, or more exactly each visit, can be a source of information for the market.

3. An empirical model of market interactions

The question we address here is the following. To what extent do the prices on this market depend on market interactions? In other words, on a market where prices are not quoted but where sellers and buyers regularly trade with different partners, can the price of one transaction be influenced by the prices of the others? The answer, from our point of view, is far from trivial. On the one hand, one might think that a daily market where prices are not posted is one where agents are linked by implicit contracts and there is little room for market interaction. On the other hand, one could argue that even if there is no clear possibility of arbitrage here, bargaining still happens. We then measure the influence of market interactions, in terms of the level of dependence of the price of a given transaction between two individuals on the prices and quantities of all other transactions involving the same individuals.[3] We postulate that the partial individual demands and the partial

[2] By regularly, we mean here buyers coming at least once a week.

[3] We thank an anonymous referee for suggesting a definition of market interactions.

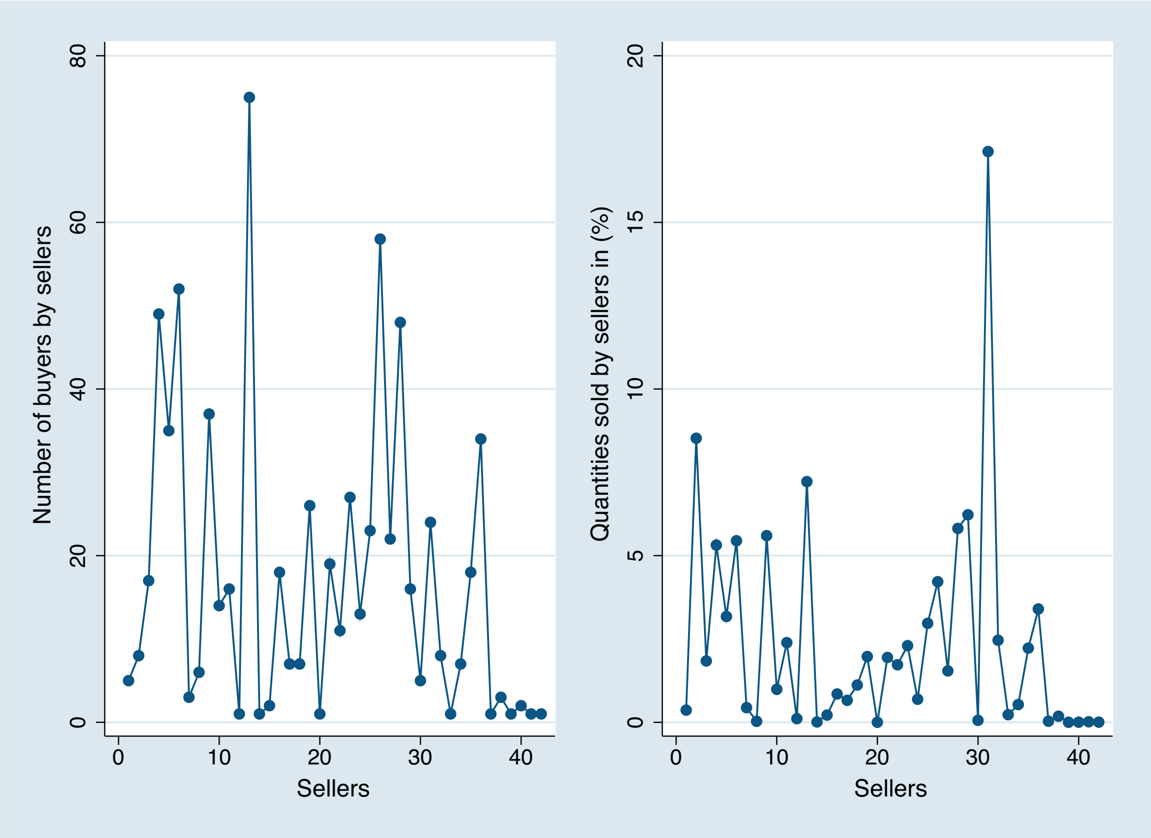

Fig. 1. There is no exact correspondence between the number of buyers met and the quantities sold.

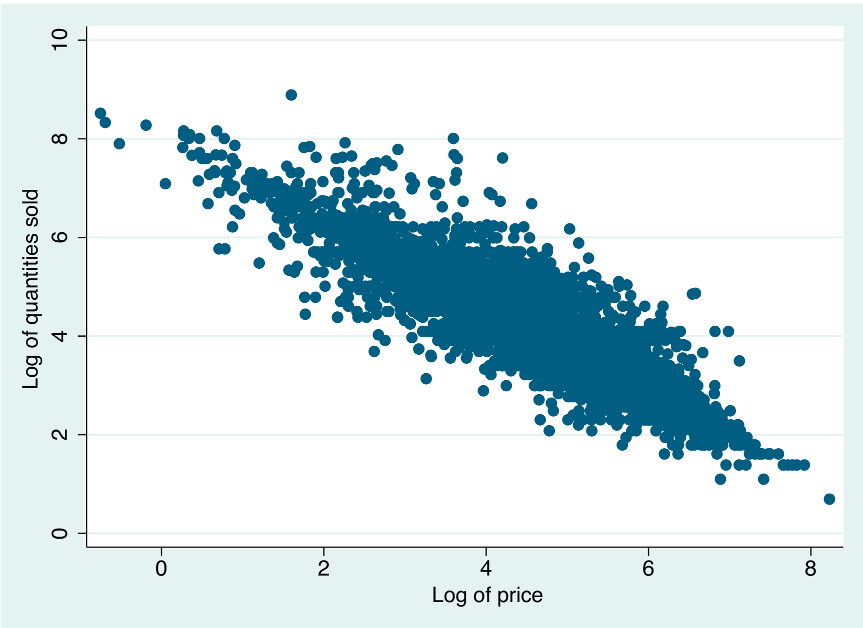

Fig. 2. There is no pure decreasing relation between the prices and the quantities sold.

individual offers depend on both the quantities transacted and the market interactions. We estimate the determinants of transaction prices through a static model and then through a dynamic one.

The following hypotheses define the market studied:

1. n sellers and m buyers who regularly meet and exchange units of a homogeneous good (we focus on the transactions concerning a certain species).
2. A day is a period of time.
3. Each transaction is the result of the intersection between a partial demand and a partial supply.
4. The supply depends on the price of the transaction, the average price the seller asks other buyers, and the sum of quantities the seller sells to other buyers.
5. The demand depends on the price of the transaction, the average price the buyer pays to other sellers, the average price the other buyers pay to the seller, the sum of quantities the buyer purchases from other sellers.

We can now write the following model:

At each time t, $t = 1, 2, \ldots, T$ a seller i with a supply $q^O_{i,j}$, $i = 1, 2, \ldots, N$ meets a buyer j with a demand $q^D_{i,j}$, $j = 1, 2, \ldots, M$.

$$q^O_{i,j} = f\left(p_{i,j}, \bar{p}_{i,k \neq j}, \sum_{l \neq j} q_{i,l \neq j}\right) \tag{1}$$

$$q^D_{i,j} = f\left(p_{i,j}, \bar{p}_{k \neq i,j}, \bar{p}_{i,l \neq j}, \sum_{k \neq i} q_{k \neq i,j}\right) \tag{2}$$

By combining Eqs. (1) and (2), we can express a transaction price in terms of other prices and quantities.

$$p_{i,j} = g\left(\bar{p}_{k \neq i,j}, \bar{p}_{i,l \neq j}, \sum_{l \neq j} q_{i,k}, \sum_{k \neq i} q_{k,j}\right) \tag{3}$$

where $p_{i,j}$ denotes the price of a transaction between a seller i and a buyer j, $\bar{p}_{k \neq i,j}$ the average price of the transactions between the buyer j and the sellers other than i, and $\bar{p}_{i,l \neq j}$ the average price of the transactions between the seller i and the buyers other than j. $\sum_{l \neq j} q_{i,l}$ denotes the sum of the quantities sold by i to buyers other than j, and $\sum_{k \neq i} q_{k,j}$ the sum of the quantities bought by j from sellers other than j.

3.1. The static case

The specification given by Eq. (3) is estimated by the Generalized Least Square Method.

$$p^j_{i,t} = \beta_1 \bar{p}^j_{k \neq i,t} + \beta_2 \bar{p}^{l \neq j}_{i,t} + \alpha_1 \sum_{k \neq i} q^j_{k,t} + \alpha_2 \sum_{l \neq j} q^l_{i,t} + \gamma_1 Y_t + \gamma_2 M_t + \gamma_3 D_t + v_{i,t} \qquad i = 1, 2, \ldots, N;$$
$$j = 1, 2, \ldots, M; \quad t = 1, 2, \ldots, T \tag{4}$$

$$v_{it} = \mu_i + \delta_{it}, \quad \mu_i \sim i.i.d.(0, \sigma^2_{\mu_i}), \quad \delta_{it} \sim i.i.d.(0, \sigma^2_\delta) \tag{5}$$

The endogenous variable is $p^j_{i,t}$, which designates the transaction price between seller i and buyer j. The model estimated is log–log, which allows us to directly interpret the estimated coefficients as elasticities. The explanatory variables are related to the influence of the time, the influence of the decisions of other individuals in terms of prices and quantities. v_{it} is the error term, which is broken down into two parts (see Eq. (5)): μ_i, which corresponds to an unobserved transaction-specific time-invariant effect (to take into account the heterogeneity of the transactions among sellers), and δ_{it}, which is an error term. $\beta_1, \beta_2, \alpha_1, \alpha_2, \gamma_1, \gamma_2, \gamma_3, \theta$ are the estimated parameters following a generalized least square estimation.

This market is daily, influenced by social customs (in Catholic countries, people usually eat more fish on Friday, which could have a repercussion on the demand and consequently on prices) and the day of the week could play a role in the determination of prices. Fishing is a gathering activity, subject to seasonality. Our sample covers three different years during which inflation was significant and fishing activity varied, following variations in European quotas, which also had a great impact on the functioning of markets. We then introduce dummy variables into the estimated equation, Eq. (4), in order to isolate the influence of the different time scales (D_t for days of the week, M_t for months, Y_t for years) and to concentrate on the determinant of prices at a given time.

3.2. A dynamic panel data model

Next we estimate a dynamic panel model to better explain the formation of transaction prices. The fact that individuals know each other could suggest that learning and memory play an important role in this market. One possible hypothesis is that repeated transactions between individuals are influenced by the past history. In that case, we might expect the endogenous variable (the price of the transactions) in our model to be clearly dependent on the lagged variable. On the contrary, a repetitive market with non-anonymous individuals could be one where there is no need for adjustment, as people have perfect information about the history of transactions. In that case, the lagged variable would have no influence on the current one, in a context of rational naïve anticipations as shown by Ezekiel (1938), quoted by Bresson and Pirotte (1995). Generally, in the related literature, the influence of the past is analyzed through an auto-regressive model, measuring the evolution of prices through the different days of the market. We therefore consider our sample as a panel of pairwise transactions, in which the time interval is the distance between two different exchanges, on two different days. It should be noted that the interval between two transactions can differ from one pair (seller/buyer) to another, some buyers being on the market every day while others are not. Eq. (6) is the dynamic form of Eq. (4).

$$p_{i,t}^{j} = \beta_1 p_{i,t-1}^{j} + \beta_2 \bar{p}_{k\neq i,t}^{j} + \beta_3 \bar{p}_{i,t}^{l\neq j} + \alpha_1 \sum_{k\neq i} q_{k,t}^{j} + \alpha_2 \sum_{k\neq j} q_{i,t}^{k} + \gamma_1 Y_t + \gamma_2 M_t + \gamma_3 D_t + \upsilon_{i,t}$$
$$i = 1, 2, \ldots, N; \quad j = 1, 2, \ldots, M; \quad t = 1, 2, \ldots, T \tag{6}$$

$$\upsilon_{it} = \mu_i + \delta_{it}, \quad \mu_i \sim i.i.d.(0, \sigma_\mu^2), \quad \delta_{it} \sim i.i.d.(0, \sigma_\delta^2) \tag{7}$$

where $p_{i,t-1}^{j}$ denotes the price of the transaction between a seller i and a buyer j the last time they met and exchanged.

Following Loayza and Schmidt-Hebbel (2000) and Schrooten (2005), we use the alternative "system GMM estimator" proposed by Arellano (1995) and Blundell (1998), which reduces the potential biases and imprecision associated with the usual difference estimator, by combining the regression in differences and the regression in levels within the same system. It is based on the estimation of a system of two simultaneous equations, one in levels (with lagged first differences as instruments) and the other in first differences (with lagged levels as instruments). As Windmeijer (2005) notes, the estimated asymptotic standard errors of the efficient two-step GMM estimator are severely downward-biased in small samples, and we therefore correct the standard errors for this bias using the method proposed by this author. We use this estimator for three main reasons. Firstly, inertia is likely to be present in daily data, and it seems useful to adopt a dynamic specification to allow for this. Secondly, the explanatory variables (such as the quantities) are likely to be jointly determined with the transaction price, and it is desirable to control for the potential joint endogeneity of the explanatory variables. Finally, there exists a possibility of unobserved transaction-specific effects correlated with the regressors, and it is important to control for such effects. All the exogenous variables included in the two specifications are used as instruments in our estimations. Finally, the two-period lag of the transaction price is only used as an instrument in the level equation.

3.3. The influence of market interactions

The estimates of Eqs. (4) and (6) are presented in Table 1.[4] Model 1 is the static model and models 2 and 3 are the dynamic ones. They were computed through an incremental process. In model 1, we begin by estimating the influence of the measured effects on the price of a pairwise transaction. These effects are captured by introducing the prices and quantities exchanged by the buyer with other sellers and by the seller with other buyers. We observe that both the prices paid by the buyer to other sellers and the prices charged by the seller to other buyers have a strong significant positive influence (1% level). Of the two, however, the prices the seller charges other buyers have a much higher impact. An increase of 1% in the prices charged to the other buyers implies an increase of 0.6% on the current transaction. It seems that when a buyer buys at high prices from other sellers, he continues to buy at high prices: these results are in line with those of Kirman and Vignes (1991), who show that while intrinsic characteristics are common knowledge, buyers with high risk aversion have no other choice than to pay the monopoly price. This is also true for sellers who appear to specialize in a certain level of prices (high or low). The hypothesis of specialization will be explored at greater length in Section 4. As we will see below, the estimation of a dynamic model helps us to determine whether these kinds of pure strategies (high prices or low prices) are continuous over time (which would define a real 'price determination profile') or stochastic, which would suggest that high-price individuals one day might become low-price individuals on another day.

Finally, we observe that the quantities sold by the seller have a strongly significant negative effect (the higher the quantities sold, the lower the price of the transaction). On the contrary, the quantities bought by buyers from other sellers have no influence on the price of a given transaction. One explanation could be that although it is not rare to find a buyer who buys different units of a same type of fish from different buyers, the frequency and the quantities exchanged are not large

[4] One of the characteristics of the estimation method used in the dynamic models is to make the fixed effects disappear. Because ρ is computed from fixed effects in the static case, we are not able to compute the same measure for the dynamic case.

Table 1
The effect of market interactions dependent variable: transaction prices (in logarithm).

Variable	Model 1	Model 2	Model 3
Lag of price	–	−0.0588 ***	−.03678 **
Price other buyers	.6013 ***	–	.4669 ***
Price other sellers	.2922 ***	–	.1806 ***
Quantity other buyers	−.06258 ***	–	−.005045
Quantity other sellers	.001029	–	.03933
Daily dummies			
Monday	−.1663	0.1239	.09938
Tuesday	−.1222 ***	−0.1732 ***	−.1409 ***
Wednesday	−.1035 ***	−0.1452 ***	−.1224 ***
Thursday	−.1163 ***	−0.1331 ***	−.1181 ***
Friday	−.1011 ***	−0.1009 ***	−.09655 ***
Saturday	Ref.	Ref.	Ref.
Monthly dummies			
January	−.05835 **	−0.0769 *	−.04588
February	−.04105 *	−0.0944 **	−.05191
March	−.05403 *	−0.0659 *	−.04108
April	−.1041 ***	−0.1437 ***	−.09993 ***
May	−.09845 ***	−0.1353 ***	−.07807 **
June	−.06572 ***	−0.1011 ***	−.05556 *
July	−.0007501	−0.0047	.03427
August	−.008023	0.0001	.01476
September	−.0453 *	−0.0587	−.02303
October	−.06448 **	−0.0942 **	−.04964
November	−.09872 ***	−0.1376 ***	−.08774 **
December	Ref.	Ref.	Ref.
Yearly dummies			
Year 1988	Ref.	Ref.	Ref.
Year 1989	.06864 ***	0.1004 ***	.0863 ***
Year 1990	−.08646 ***	−0.0476 *	−.05482 **
Intercept	.8696 ***	−0.0008	.0007032
SigmaU	.2545		
SigmaE	.3769		
Sigma	.4547		
Rho	.3132		
N	15473	7418	7369
Sargan test		$chi^2(452) = 433.03$ $Prob > chi^2 = 0.7316$	$chi^2(438) = 426.89$ $Prob > chi^2 = 0.6391$
Arellano Bond test AR (1)		$z = -36.94$ $Pr > z = 0.0000$	$z = -36.99$ $Pr > z = 0.0000$
Arellano Bond test AR (2)		$z = -1.57$ $Pr > z = 0.201$	$z = -0.97$ $Pr > z = 0.3311$

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

enough to influence the estimation. Unsurprisingly, we can observe the influence of different seasonal variations (yearly, monthly and daily). Prices are lower in April and November. They were lower in 1988 and 1989 than in 1990. The dummy variables capture the effects of economic cycles like inflation. The prices also vary through the week.

The dynamic estimation (models 2 and 3) produces some important results. In model 2, when the estimation only includes the lagged price, this effect is negatively significant at 1%: it should be noted, here, that the effect is very low (the price is decreased by 0.05% compared to the price of the previous exchange). This result implies that the past price does matter, but only to a very limited extent. The results obtained with the static model can still be observed, at least as far as the price effects are concerned. Their influence is lower (from 0.6% to 0.46% for the effect of the prices the seller charges other buyers). The different time scales (days of the week, months and years) still appear to greatly influence the transaction prices.

We have now verified that, on this market, the price of a transaction depends on the prices of the other transactions taking place at the same time. But the significant results we obtain are quite weak. The ρ coefficient (Rho, end of Table 1) has a very low value (around 0.31), suggesting that a large part of the price-formation phenomenon is neglected by our estimation. One explanation could be that we are studying people who are heterogeneous (both sellers and buyers) in terms of strategic behavior regarding both prices and quantities exchanged. Looking at the results of the dynamic estimations, it may seem surprising to find so weak an effect of past price, in a market where people know each other. The fact that the price of a given exchange between two people depends so little on the prices of past exchanges between the same two people could suggest the existence of "price determination profiles": there is no clear learning effect, because pairings are not random,

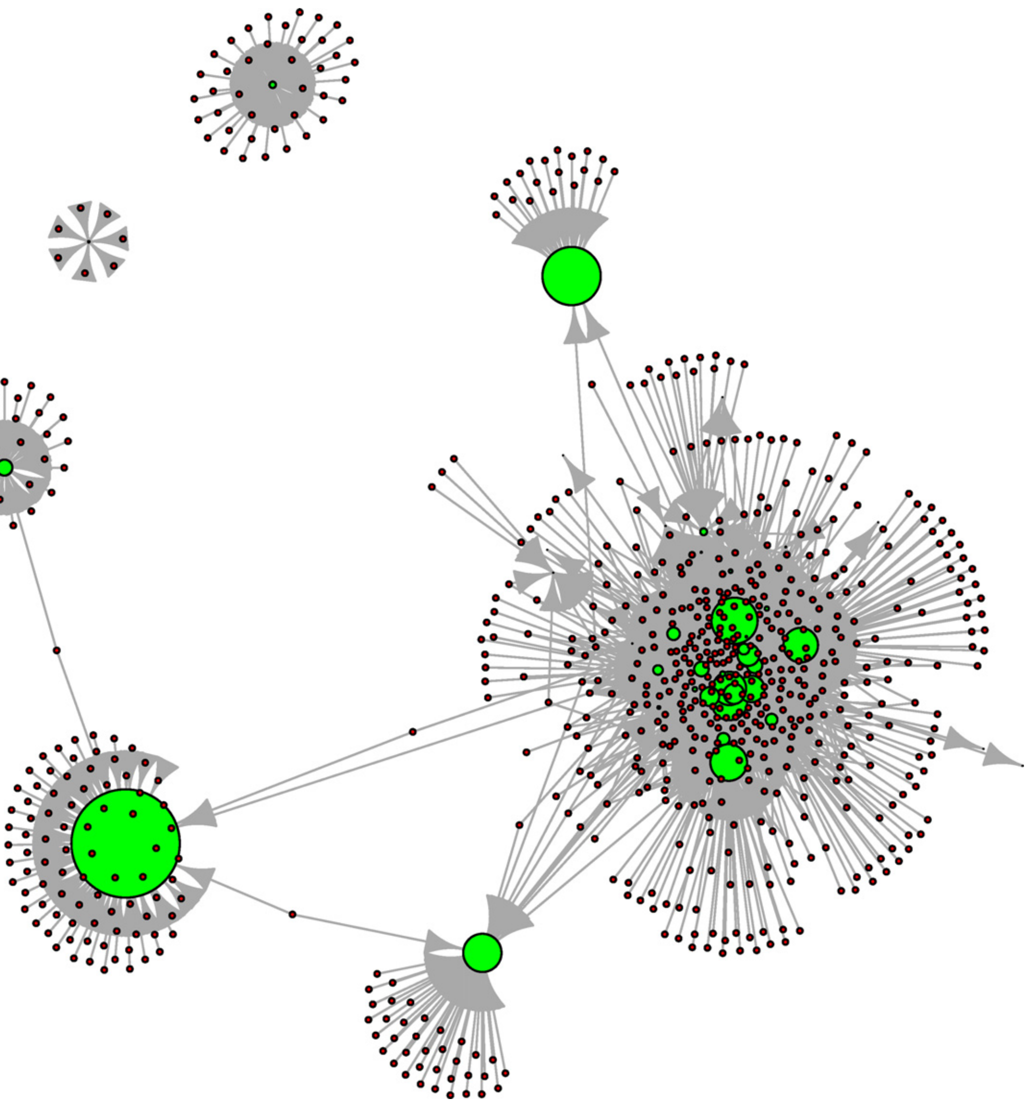

Fig. 3. The bi-partite network of sellers (green) and buyers (red) in the fish market. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

people know each other and are identified by well-defined selling or buying strategies. It is now important to explore the influence of non market effects.

4. Network analysis

The results presented in Section 3 suggest that the determinants of price formation depend on something more than market interactions. In a world where people meet daily and know each other, we now hypothesize that traders take into account the identity and characteristics of their partners and that links between individuals matter. Considering people as distributed on a network and linked by the graph of transactions, we explore the determinants of differences in strategy. We first consider a buyer–seller network, where buyers and sellers are heterogeneous in quantities traded. To better understand the influence of buyers' strategies (loyal to a small number of sellers or shopping around, visiting a large number) on the formation of prices, we then consider a seller–seller network, as the projection of the buyer–seller network, and explore the properties of centrality. From a technical point of view, the role of centrality will be easier to interpret in a homogeneous network. From an economic point of view, it is interesting to relate centrality, market power and intensity in competition. Here, the most central sellers are those who share the largest number of buyers with other sellers, *i.e.*, those who experience the highest level of competition.

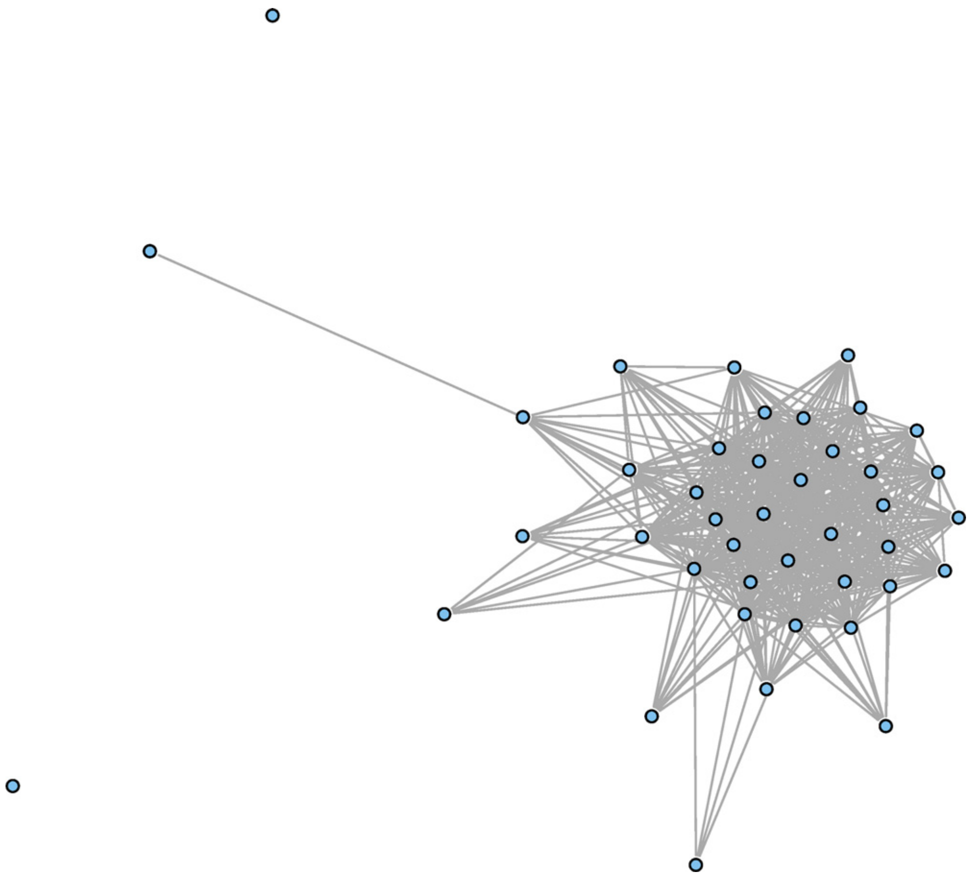

Fig. 4. The seller–seller network in the fish market: two sellers are linked when they share at least one buyer.

4.1. The network design

Fig. 3 illustrates, through a bipartite network representation, the structure of the links between buyers and sellers. We only consider the buyers who are present more than three times on the market during the period studied. On this network, a link is a transaction.

The buyer–seller network suggests that on the Marseilles fish market, some sellers share the same buyers while others sell exclusively to loyal buyers. This pattern seems stable through the different years (the details for the different years are presented in the annex*** in Appendix B). Clearly, two different sub-markets appear, one where buyers visit a lot of sellers (and the sellers share a lot of buyers), and another where the sellers have their own exclusive buyers. In what follows, we refer to the first category as 'nomad' and the second category as 'loyal'. In fact, six sellers appear to be isolated from the rest of the market. These six sellers represent 2460 transactions (compared to 17,927 for the rest of the market). On the two sub-samples ('six sellers' and 'all the other sellers'), both the distributions of prices and quantities are fat-tailed with a wide spread. The six sellers charge a lower average price (1.07, compared to 1.85 charged by the others) but sell a total quantity of around 6 tonnes (compared to about 10 tonnes for the rest of the market). 50% of 'nomad' buyers purchase between 6 and 18 k per transaction. The quantities exchanged by 'loyal' agents are between 5 and 17 k. As for the prices, they range between 37 cents and 1.18 francs (per kilo) on the 'loyal' market and between 50 cents and 6.90 francs (per kilo) on the other market. At this stage, it is not possible to characterize the different types of behavior ('loyal' or 'nomad') in terms of differences in the quantities exchanged. As far as prices are concerned, we observe that the range of the distribution is higher for the 'nomads'.

To further investigate the influence of strategies, we now consider a homogeneous seller–seller network. Two sellers are linked if they share the same buyers. The idea here is that a buyer can be an 'information driver' going from one seller to another. The topology of the network should give us some indication of the way individuals behave, particularly by computing a centrality coefficient. Eq. (8) defines the link between two sellers.

$$l_{i,j}^{t} = \begin{cases} 1 & \text{if } \exists k \in M | (q_{i,k}^{t} \neq 0 \text{ and } q_{j,k}^{t} \neq 0) \\ 0 & \text{else} \end{cases} \qquad \forall i, j \quad j \neq i, \quad i, j \in N \tag{8}$$

Table 2
The effect of centrality. Dependent variable: transaction prices (in logarithm).

Variable	Model 1	Model 2	Model 3	Model 4
Lag of price	–	–	−.05929 ***	.03737
Centrality	1.943 ***	.4959*	3.273 ***	3.464**
Price other buyers	–	.6005 ***	–	.4783 ***
Price other sellers	–	.28 ***	–	.1606 ***
Quantity other buyers	−.1609 ***	−.06221 ***	–	−.01453
Quantity other sellers	−.0232	−.009244	–	.05094**
Weekly dummies				
Monday	−.3206 **	−.1145	.1261	.003015
Tuesday	−.1602 ***	−.1152 ***	−.1756 ***	−.1352 ***
Wednesday	−.1187 ***	−.08867 ***	−.1472 ***	−.109 ***
Thursday	−.1433 ***	−.1093 ***	−.1358 ***	−.1292 ***
Friday	−.1137 ***	−.09465 ***	−.1052 ***	−.1049 ***
Saturday	Ref.	Ref.	Ref.	Ref.
Monthly dummies				
January	−.06357 *	−.06314 *	−.06889 *	−.04928
February	−.03924	−.0409 **	−.08652 **	−.04598
March	−.07315 *	−.07091 *	−.05964	−.0727 **
April	−.1293 ***	−.1055 ***	−.1379 ***	−.09318 ***
May	−.1455 ***	−.1049 ***	−.1273 ***	−.07875 *
June	−.07946 ***	−.07261 ***	−.09241 **	−.05954 **
July	−.00888	−.01627	.0005817	−.01709
August	−.004952	−.004258	.007937	.02815
September	−.03864	−.04687 **	−.05148	−.0304
October	−.08954 ***	−.07105 ***	−.09334 **	−.02722
November	−.1224 ***	−.1044 ***	−.135 ***	−.09137 *
December	Ref.	Ref.	Ref.	Ref.
Yearly dummies				
Year 1988	Ref.	Ref.	Ref.	Ref.
Year 1989	.08739 ***	.06303 ***	.09906 ***	.07766 ***
Year 1990	−.0899 ***	−.07823 ***	−.05423 *	−.03338
Constant	4.163 ***	.5326**	−.0004	.00089**
sigmaU	.4853	.2391	–	–
SigmaE	.4221	.2535	–	–
Rho	.5694	.3108		–
N	11789	11789	7369	7369
Sargan test			$chi^2(435) = 394.93$ $Prob > chi^2 = 0.9162$	$chi^2(439) = 396.9$ $Prob > chi^2 = 0.9262$
Arellano Bond test AR (1)			$z = -36.39$ $Pr > z = 0.0000$	$z = -37.00$ $Pr > z = 0.0000$
Arellano Bond test AR (2)			$z = -2.56$ $Pr > z = 0.0105$	$z = -0.64$ $Pr > z = 0.5228$

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

where N denotes the set of sellers; M, the set of buyers; $q^t_{i,k}$, the quantity exchanged at time t between a seller i and a buyer k; and $q^t_{j,k}$, the quantity exchanged between a seller j and a buyer k. $l^t_{i,j}$ defines a link between two sellers.

In Fig. 4, two sellers are linked if they have at least one buyer in common. We obtain a network with 42 nodes and 515 links and calculate a measure of centrality for sellers. Clearly, to be central, a seller not only needs to get a lot of different buyers, but also to get a lot of different nomad buyers. Looking at some classical network statistics, we observe that the clustering coefficient (0.837) is higher than the density coefficient (0.598), which suggests a non-random network, at least in the sense of Erdös and Rényi (1960). Clearly, the buyers do not transact at random. The assortativity (0.028) is weak but positive, which suggests that sellers who have a lot of buyers share these buyers with other sellers who also have a lot of buyers.

The position of a seller is particularly important, since it represents the intensity of his links with the buyers. The more central the seller's position, the more buyers he has, but also the more nomad buyers. In Section 4.2, we explore the effect of this position on the outcome of the transactions.

4.2. The influence of centrality

This section investigates the role of the individuals' positions in the network. This is evaluated by the eigenvalue centrality measure (c_i) as computed by Bonacich (1987). The centrality of a node is its summed connections to others, weighted by

Table 3
The effect of centrality on nomadic and loyal strategies Dependent variable: transaction prices (in logarithm).

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Nomads					
Centrality	–	1.7914 ***	0.2607	0.2522	–
Price other buyers	–	–	0.6209 ***	0.6447 ***	0.6449 ***
Price other sellers	–	–	0.2705 ***	0.2728 ***	0.2780 ***
Quantity other buyers	−0.1733 ***	−0.1721 ***	−0.0537 ***	–	–
Quantity other sellers	0.0055	−0.0252 *	−0.0051	–	–
Constant	5.8565 ***	4.3587 ***	0.6220 ***	0.2173	0.4308 ***
N	17927	17927	17927	17927	17927
SigmaU	0.4740	0.4715	0.2395	0.2437	0.2439
SigmaE	0.4172	0.4172	0.3694	0.3694	0.3694
Rho	0.5635	0.5609	0.2959	0.3034	0.3035
Sigma	0.6314	0.6296	0.4402	0.4426	0.4426
Loyals					
centrality	–	0.3326 ***	0.0057	−0.0273	–
Price other buyers	–	–	0.9422 ***	0.9844 ***	0.9844 ***
Price other sellers	–	–	0.0104	0.0170	0.0180
Quantity other buyers	−0.8947 ***	−0.8988 ***	−0.0543 ***	–	–
Quantity other sellers	−0.0774 ***	−0.0873 ***	−0.0083	–	–
Constant	8.9428 ***	8.9190 ***	0.5098 ***	0.0001	−0.0143
N	2460	2460	2460	2460	2460
SigmaU	0.3172	0.3135	0.1378	0.1482	0.1478
SigmaE	0.3402	0.3402	0.1376	0.1382	0.1382
Rho	0.4650	0.4592	0.5009	0.5346	0.5334
Sigma	0.4651	0.4626	0.1947	0.2026	0.2024

* Significant at 10%. **Significant at 5%.
*** Significant at 1%.

their own centralities. It measures the importance of a node in a network. Connections to high-scoring nodes contribute more to the score of the node in question than an equal number of connections to low-scoring nodes. In what follows, we add centrality as a further regressor to improve the fit of the econometric model previously estimated.

The influence of centrality is estimated through Eq. (9).

$$p_{i,t}^{j} = \theta c_{i,t} + \beta_1 \bar{p}_{k\neq i,t}^{j} + \beta_2 \bar{p}_{i,t}^{k\neq j} + \alpha_1 \sum_{k\neq i} q_{k,t}^{j} + \alpha_2 \sum_{k\neq j} q_{i,t}^{k} + \gamma_1 Y_t + \gamma_2 M_t + \gamma_3 D_t + v_{i,t}$$

$$i = 1, 2, \ldots, N; \quad j = 1, 2, \ldots, M; \quad t = 1, 2, \ldots, T \tag{9}$$

$$v_{it} = \mu_i + \delta_{it}, \quad \mu_i \sim i.i.d.(0, \sigma_{\mu_i}^2), \quad \delta_{it} \sim i.i.d.(0, \sigma_{\delta}^2) \tag{10}$$

Table presents the results of two static specifications (models 1 and 2) and two dynamic ones (models 3 and 4). Because of small values, the centrality variable is not expressed in logarithm, unlike the others. A first observation is that the ρ values are higher in these specifications than they were in the estimation of Eq. (4). In the first static estimation (model 1, Table 2), the correlation coefficient is very near to 0.57: the effect of centrality is strongly significant (1%) when isolated from the influence of the other variables. In model 2 and model 3, the significance is weaker (at 5%) but still present: the more central a seller, the higher the prices he charges. The idea that sellers who share a lot of buyers with other sellers (i.e. sellers in a more competitive environment) will charge higher prices is not intuitive. We interpret the centrality coefficient in terms of market power and what Cook and Yamagishi (1992) call exchange ratios. The sellers who are less central are also those who have bigger quantities to sell and less opportunities in terms of buyers. This result is in line with Corominas-Bosch (2004), who show that when there is competition on a market, the short side has the power. An alternative explanation could be that 'loyal' sellers[5] have a lower risk than the others because the level of competition is lower.

One of the results of the two dynamic specifications is that the lagged effect is significant and negative (1%) when we do not control for the other explanatory variables, except the centrality variable which is also strongly significant. In model 4, when we introduce all the exogenous variables, the lagged effect disappears and the centrality effect is weaker. We again find the strong 'prices of other buyers' and 'prices of other sellers' effects. We believe that these last two effects absorb part of the lagged price effect. Finally, we observe that the dummy variables (years, months and days) remain significant.

[5] In what follows, 'loyal' buyers or sellers refers to thoseagents who are mainly involved in loyal matching: likewise, 'nomad' buyers or sellers denotes those who are mainly involved in nomadic matching.

Clearly, there exists a robust centrality effect and a less robust past history effect on this market. The persistent significance of centrality and the particular network structure as it appears in Figs. 3 and 4 leads us to drive the estimations (cf. Table 2) on two different sub-populations distinguished according to their level of centrality. The results are presented in Section 4.3.

4.3. The advantage of being loyal

We now estimate five different static specifications on two different samples of individuals, one composed of sellers involved in loyal matchings (*i.e.*, exchange with loyal buyers), the other composed of sellers involved in nomadic matchings (*i.e.*, exchange with nomad buyers). The sample is split on the basis of observation of the buyer–seller network. Six sellers clearly appear as isolated and their centrality coefficients in the seller–seller network are much lower than the others. The 'loyal' sellers have a centrality coefficient between 0.00 and 0.28, whereas the 'nomads' have a centrality coefficient between 0.40 and 1.00. The results are presented in Table . For both the nomadic and the loyal populations, the ρ coefficients exhibit higher values than in the estimation presented in Section 3. The higher values obtained in model 2 show that the centrality variable is strongly significant for both the nomad and the loyal populations, confirming the pertinence of considering two sub-samples. However, this effect is greater for nomads than it is for loyal individuals, showing that nomads are less homogeneous in their behavior than loyals are. In models 3 and 4, the price effects are strongly significant. Concerning the positive effect of the other buyers' prices, the influence on the loyal population is stronger (the effect is very near to one) than it is on the nomad population: for the loyals, an increase in the price of a transaction is quasi-perfectly passed on to the prices of the others. Remember that the price distribution is wider on the 'nomadic' sub-sample. These two facts suggest that although prices are lower on average, a 'loyal' strategy can be safer for a seller: all the price increases are perfectly absorbed by all the transactions, which is not the case on the nomad side. The other sellers' prices are positively significant in the case of 'nomad' transactions, and not significant in the case of 'loyal' transactions, reflecting the specific behaviors of the two sub-populations. We find evidence of a classical negative relationship between price and quantity for both loyals and nomads. The influence of dummies is also significant, but because they are qualitatively the same as in the previous estimations, they are not presented in Table 3.

5. Conclusion

This article seeks to explain the formation of transaction prices on a decentralized market, where agents are non-anonymous and the good is perishable, namely the fish market of Marseilles. Preliminary descriptive results suggest that the pairings are not random on this market, and that individual links can influence outcomes. An econometric model measuring the effects of market interactions on the outcome of exchanges supports this intuition. Including centrality as a further regressor improves the fit with respect to a model where the price of a transaction just depends on the prices of other transactions and on the exchanged quantities. We thus highlight the fact that market interactions are not enough to explain price dispersion. We also point out the economic paradox that the higher the level of competition among sellers, the higher the prices. The explanation is that on this market, both buyers and sellers adopt pure 'nomad' or 'loyal' strategies, evidenced by the number of people they meet. These results are robust in a dynamic analysis which also reveals that past prices have a slight negative influence on current prices. On average, loyal buyers pay lower prices than nomads: this phenomenon is partly due to the fact that loyal buyers deal in higher quantities per transaction than the nomads. For the loyals, an increase in the price of a transaction is quasi-perfectly passed on to the prices of the others. This suggests that stable links make the market safer for a seller. The history of interactions also negatively influences prices. Past prices have a negative effect on current ones. Clearly, on this market, being loyal brings some advantages to a buyer. Despite appearances, it can also be a good solution for a risk-adverse seller.

Acknowledgements

The authors are grateful to Alan Kirman, Sandro Sapio and two anonymous reviewers for helpful and stimulating comments. Special thanks also go to Georges Bresson for fruitful discussions at an early stage of the present work.

Appendix A. Descriptive statistics

Table A.4 presents some descriptive statistics on the main variables describing the data set used in this article. Fig. A.5 illustrates the volatility of prices during a particular week.

Table A.4
Descriptive statistics on the main variables used in the estimated models.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Prices	20387	175.6814	157.2281	.4712	3750
$p^{j}_{k\neq i,t}$	20387	175.6814	75.4488	5.3333	1187.5
$p^{k\neq j}_{i,t}$	20387	175.6814	141.1737	.4712	2750
Weights	20387	78.9568	157.6759	2	5325
$q^{k\neq j}_{i,t}$	20387	148.3359	193.5013	4	5325
$q^{j}_{k\neq i,t}$	20387	2364.669	1820.337	5.3333	15086.36
$r_{i,t}$	20387	4.4182	1.6606	.034	6.771
$r_{j,t}$	20387	.3108	.1959	.034	.7825

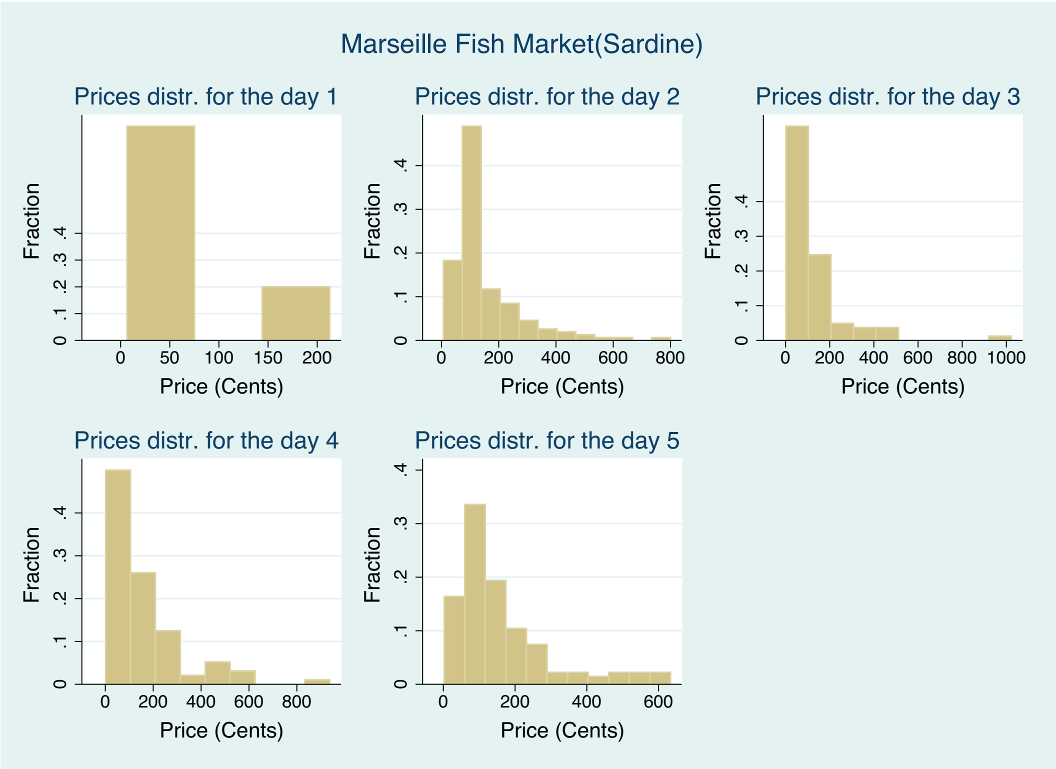

Fig. A.5. The daily price distribution on the week 11/06/90–16/06/90.

Appendix B. Network statistics

Fig. B.6 represents the distribution of degrees among the sellers Figs. B.7–B.9.

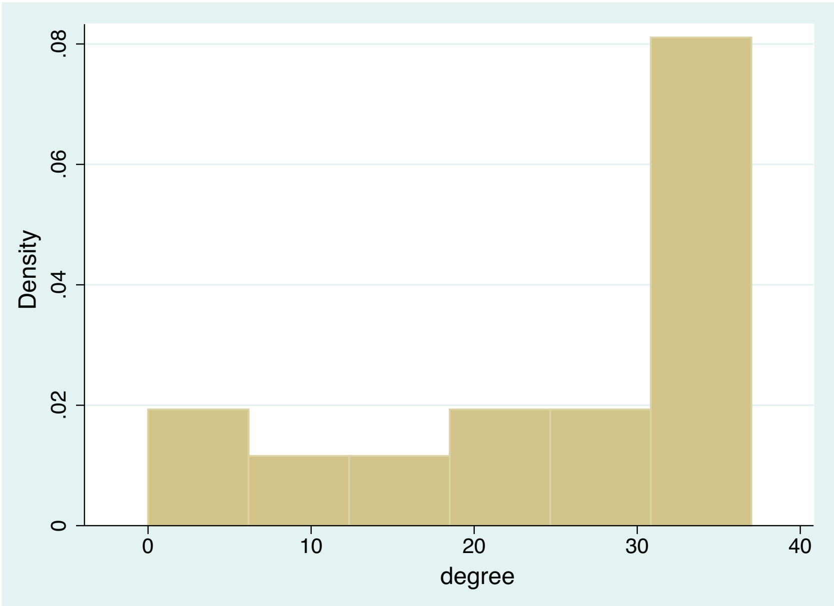

Fig. B.6. The non-linear relation between prices and quantities, June 1988.

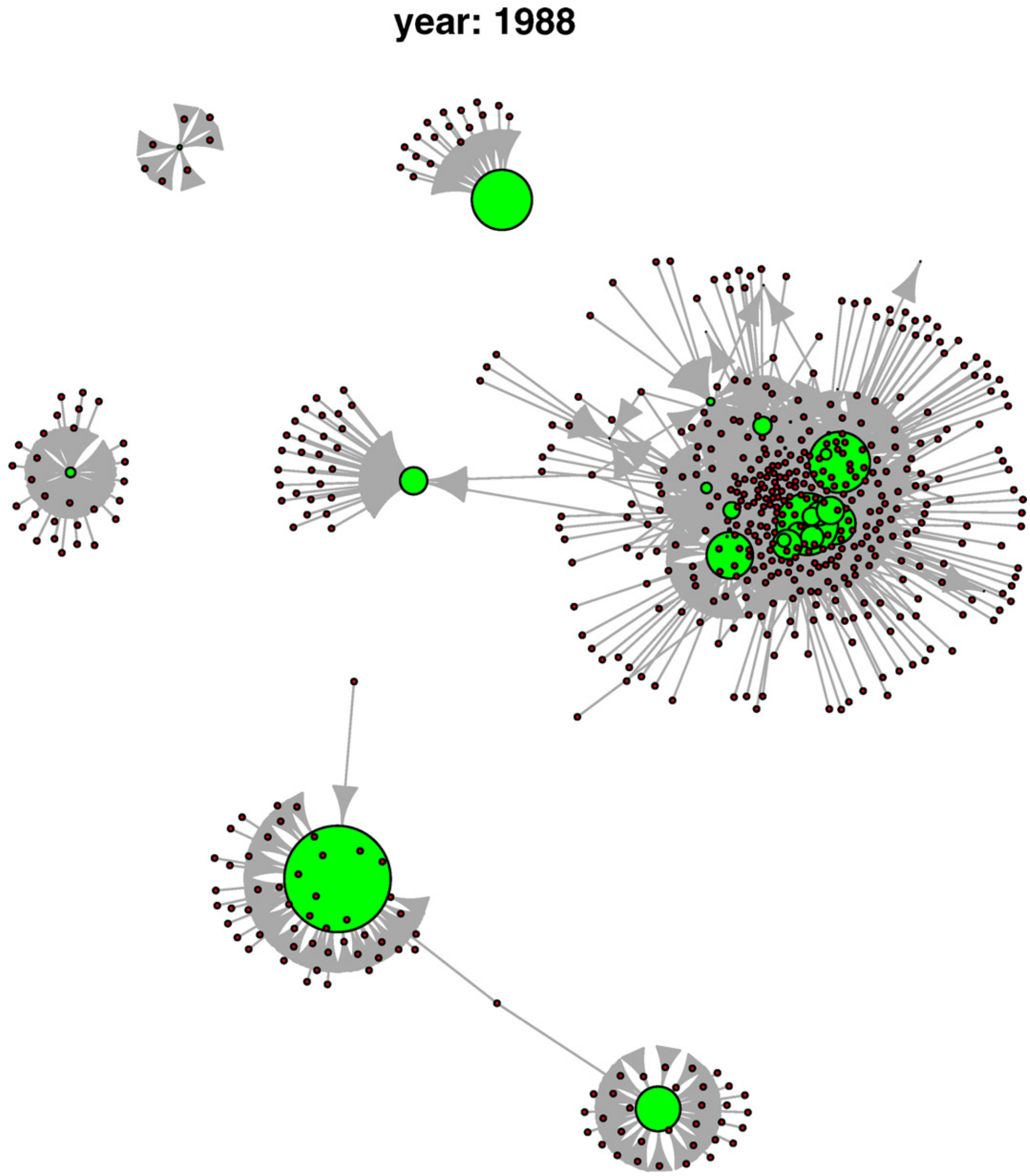

Fig. B.7. Distribution of degrees among sellers.

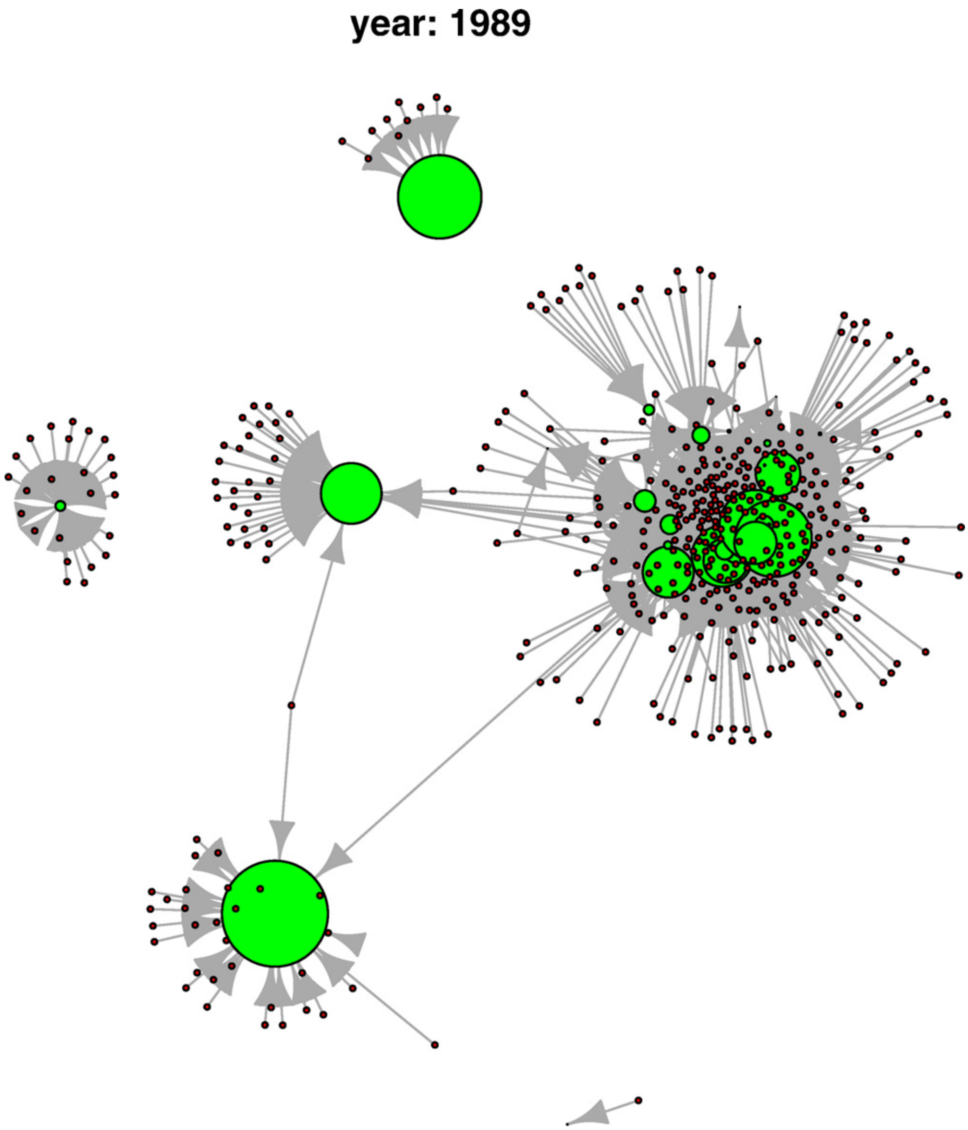

Fig. B.8. The buyer–seller network for the year 1988.

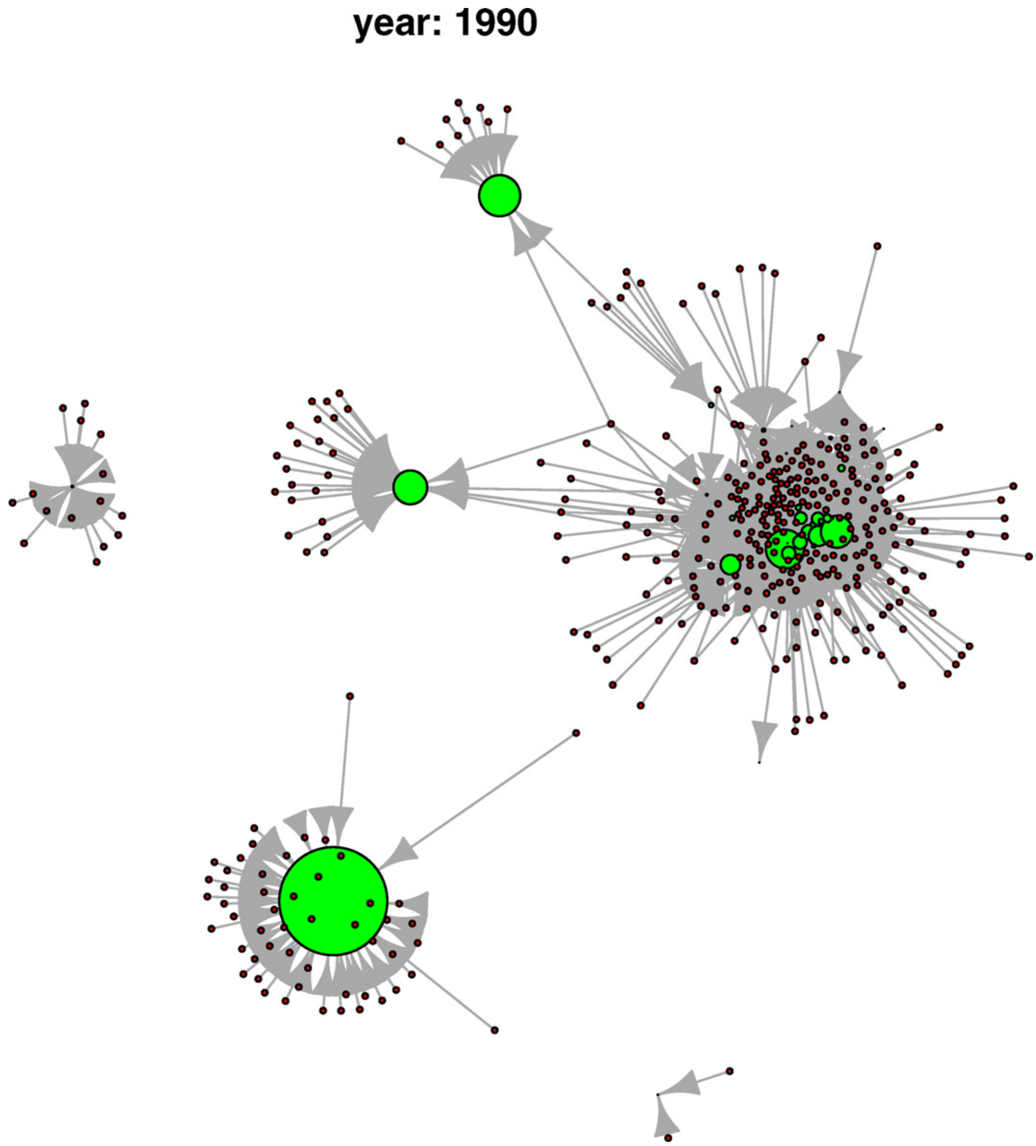

Fig. B.9. The buyer–seller network for the year 1989.

References

Arellano, B., 1995. Another look at the instrumental variable estimation of error-components models. Journal of Econometrics 68, 29–51.
Blundell, B., 1998. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics 87, 115–143.
Bonacich, P., 1987. Power and centrality: a family of measures. American Journal of Sociology 92, 1170–1182.
Bresson, G., Pirotte, A., 1995. Econométrie des séries temporelles: théories et applications. Presses Universitaires de France.
Brown, M., Falk, A., Fehr, E., 2004. Relational contracts and the nature of market interactions. Econometrica 72, 747–780, N 3.
Casella, A., Rauch, J., 2002. Anonymous market and group ties in international trade. Journal of International Economics 58 (1), 19–47.
Cook, K., Emerson, R., Gillmore, M., Yamagishi, T., 1983. The distribution of power in exchange networks: theory and experimental results. American Journal of Sociology 89, 275–305.
Cook, K., Yamagishi, T., 1992. Power in exchange networks: a power-dependence formulation. Social Networks 14, 245–265.
Corominas-Bosch, M., 1999. On Two-sided Network Markets. Ph.D. thesis. Universitat Pompeu Fabra.
Corominas-Bosch, M., 2004. Bargaining in a network of buyers and sellers. Journal of Economic Theory 115, 35–77.
Erdös, P., Rényi, A., 1960. On the evolution of random graphs. Publication of the Mathematical Institute of the Hungarian Academy of Sciences 5.
Ezekiel, M., 1938. The cobweb theorem. The Quarterly Journal of Economics 52 (2), 255–280.
Goyal, S., Joshi, S., 2003. Networks of collaboration in oligopoly. Games and Economic Behavior 43, 57–85.
Graddy, K., 1995. Testing for imperfect competition at the fulton fish market. Rand Journal of Economics, The Rand Corporation 26, 75–92.
Graddy, K., 2006. Markets: the Fulton fish market. Journal of Economic Perspectives 20, 207–220.
Hochberg, Y., Ljungqvist, Y., 2007. Whom you know matters: venture capital networks and investment performance. The Journal of Finance 62, 251–301.

Jackson, M., 2003. The stability and efficiency of economic and social networks. In: Sertel, M., Koray, S. (Eds.), Advances in Economic Design. Springer-Verlag, Heidelberg, pp. 319–362.
Jackson, M., 2008. Social and Economic Networks. Princeton University Press, Princeton.
Jackson, M., 2010. An overview of social networks and economic applications. In: Benhabib, J., Bisin, A., Jackson, M. (Eds.), The Handbook of Social Economics. Elsevier/ North Holland, New York, pp. 511–585.
Jackson, M., Watts, A., 2002. The evolution of social and economic networks. Journal of Economic Theory 71, 44–74.
Kirman, A., Vignes, A., 1991. Price dispersion. theoretical considerations and empirical evidence from the Marseille fish market. In: Arrow, K. (Ed.), Issues in Contemporary Economics. Macmillan, London, pp. 160–185.
Kosfeld, M., 2004. Economic networks in the laboratory: a survey. Review of Network Economics 3, 20–42.
Kranton, R., Minehart, D., 2000. Competition for goods in buyer–seller networks. Review of Economic Design 5, 301–331.
Kranton, R., Minehart, D., 2001. A theory of buyer–seller networks. American Economic Review 91, 485–508.
Loayza, Schmidt-Hebbel, S., 2000. What drives private saving across the world? Review of Economics and Statistics 82, 165–181.
Marshall, A., 1930. Principles of Economics, 8th ed. Mac Millan and Co., London.
Pareto, V., 1906. Manuel d'Economie Politique. MacMillan, London.
Powell, W., White, D., Koput, K., Owen-Smith, J., 2005. Network dynamics and field evolution: the growth of interorganizational collaboration in the life sciences. American Journal of Sociology 110 (4), 1132–1205.
Rauch, J., 2001. Business and social networks in international trade. The Journal of Economic Literature 39, 1177–1203.
Schrooten, M., Stephan, S., 2005. Private savings and transition: dynamic panel data evidence from accession countries. Economics of Transition 13, 287–309.
Sorenson, O., Stuart, T., 2001. Syndication networks and the spatial distribution of venture capital investments. American Journal of Sociology 106 (6), 1546–1588.
Thornton, 1869. On Labour. MacMillan, London.
Wang, P., Watts, A., 2006. Formation of buyer–seller trade networks in a quality-differentiated product market. Canadian Journal of Economics 39, 971–1004.
Weisbuch, G., Kirman, A., Herreiner, D., 2000. Market organization and trading relationships. The Economic Journal, 411–436.
Windmeijer, F., 2005. A finite sample correction for the variance of linear efficient two-step G.M.M. estimators. Journal of Econometrics 126, 25–51.