The Emergence and Impact of Market Institutions: 
The Market for Fish and Other Perishable 
Commodities

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Price sensitivity to supply traded under alternative mechanisms in the New England Fish Industry

David Genesove (M.I.T.)

The New England fishing industry from 1982-1992 demonstrates the effect of different trade mechanisms on price determination. Prices in Gloucester are more responsive to changes in supply landed in Boston than to supply landed in Gloucester itself. The underlying cause for this phenomenon lies in the different mechanisms used in the two ports - an auction in Boston, long-term non-contractual relationships in Gloucester -, and the proximate cause in the use of the Boston price as an informal index for the negotiated price in Gloucester. This pricing convention makes auction supply more “high-powered” than supply traded under long-term, bilateral relationships.1

1.1 Introduction

Gloucester is a fishing port, about forty-five minutes northeast of Boston. In the 1980s and early 1990s, it landed more groundfish2 than any other

1For provision of data and other assistance, much thanks are due to Dr. Eugene Heyerdahl and Ms. Joan Palmer of the National Marine Fisheries Service, and Mr. Dennis Frappier of the Portland Fish Exchange. Funding from Sea Grant is gratefully acknowledged. I am very grateful to Jim Wilson for his help throughout this project. Thanks to discussants Tim Bresnahan (1994 NBER summer workshop in I.O.) and Giovanni Dosi (2007 DIME Workshop on the Market for Fish and other Perishable Commodities).

2The principal groundfish in New England are cod, haddock, redfish, hake, pollock, cusk and wolffish. Flounder is sometimes counted as groundfish as well, and I will mean groundfish to include flounder in this paper. Cod is by far the most important species in New England, and in Boston and Gloucester in particular.
port in the United States. Most of the fresh groundfish landed in Gloucester is subsequently trucked to Boston for processing. Groundfish is also landed in Boston itself, though over that same period the volume of groundfish landed there was but half that of Gloucester’s, as competition from higher valued economic activity forced vessels and crews out of that once predominant fishing port. The vessels from these two ports fish in the same waters: groundfish are found most plentiful in the Georges Bank and other neighbouring offshore banks about a day’s steam northeast of the two ports.

The ex-vessel price in Gloucester obeys the most basic law of supply and demand: an extra 100,000 pounds of cod landed in that port reduces the Gloucester price by one cent. But an equal amount of cod landed in Boston reduces the Gloucester price by three cents. The ex-vessel price in Boston behaves similarly. That extra 100,000 pounds, if landed in Gloucester, would reduce the Boston price by two cents; if landed in Boston, it would reduce the Boston price by six cents. These numbers illustrate three basic facts common to prices of all groundfish species:

1. The Gloucester price is more responsive to Boston landings than to changes in it own landings;
2. The Boston price is more responsive to its own landings than to Gloucester landings;
3. The Boston price is more responsive than the Gloucester price to landings in either port.

Taken together, these observations demonstrate the effect of alternative trade mechanisms on price formation.

The first observation is inconsistent with perfect competition. This is true whether or not one regards the two ports as belonging to one, structurally integrated market. If transportation costs exceed the difference in the ports’ autarky prices, making trade across them unprofitable, then small changes in supply conditions in Boston should leave the price in Gloucester unchanged. Otherwise, when transportation costs are small enough for trade to take place across ports, increases in supply from either port should affect price equally.3

3See Spiller and Huang (1986) for a discussion of the autarky and arbitrage regimes for two spatially separated markets. We do not usually think of perfect competition as providing us with functional form restrictions. But, in fact, it does. If demand is \( D(p) \), and the two sources of supply are \( S_1 \) and \( S_2 \), then equilibrium price in the second regime is \( p = D^{-1}(S_1+S_2)/f(S_1+S_2) \); this is more restrictive than the general form \( p = f(S_1, S_2) \).
Why, then, is there a differential effect on price? I argue that the cause must lie in the different trade mechanisms that are used in the two ports. Boston has an auction. Gloucester does not. In Boston, all dealers gather together at the New England Fish Exchange building every weekday morning for about an hour to bid on that day’s landings in simultaneous oral, ascending auctions for each boat’s catch of each species. In contrast, buyers in Gloucester have long-term, non-contractual relationships with vessels that predetermine the allocation of fish among dealers. Evidently, the effect on price of supply traded under long term relationships falls far short of the price effect of supply traded through centralized exchanges. Market participants’ own description of the pricing procedure in Gloucester makes explicit Boston trades’ domination of the market. The Gloucester price is said to be “set in Boston”.4 They mean by that claim that on a given day dealers and vessels in Gloucester quote a price that is that morning’s auction price less some varying amount. A dealer might quote “five cents off Boston board”, for example. Trades that are consummated before the Boston price is established or made known may even be indexed to that price.

This pricing convention is an obvious response to the mode of trade in Gloucester. Locked in bilateral relationships, vessel and dealer must find some way to establish a price, and pricing according to a publicly disseminated auction price is an obvious response. The benefit to doing so is the time saving on negotiations, and, their necessary prelude, gathering information on market conditions. Its consequence and social cost is the failure of the price in Gloucester to fully reflect variations in its own supply.

The second observation – that the Boston price is more responsive to variations in its own supply than to Gloucester’s – is not of itself inconsistent with perfect competition. That model would interpret the differential sensitivity to the two sources of supply as evidence that the two ports are typically in an autarky regime. But descriptions of the industry clearly belie that conclusion. The two ports appear to be highly structurally integrated. (By “structurally integrated”, I mean the extent by which a competitive equilibrium in this industry would be characterized by the arbitrage regime.) Only a very small part of the fish that is landed in Gloucester stays in Gloucester. Some is first processed there and then shipped elsewhere, though as time goes by less processing is done in Gloucester, and more in Boston. The rest is either transported to Boston (at a cost of about

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4This appears to be a universally held opinion. It was stated to me by dealers and port agents, and is claimed by a number of more informed observers of the market, including Wilson (1980) and Peterson.
3 cents a pound,\(^5\) or 5 percent of the average price of cod), for processing, consumption, and/or further distribution outside of Boston, or transported directly to end-users elsewhere. Of course, even in the later case it will face competition from Boston fish at the end-user stage. Georgiana, Dirlam and Townsend (1993) claim that “there is little doubt that most groundfish landed in Gloucester is trucked to Boston for processing”, and FMP (1985, p. 3.45) concurs, noting that the small amount of fresh cod and haddock processed in Gloucester is destined for the local market.

Under these circumstances, one would expect prices in Boston to be much more responsive to Gloucester supply. Demand at the auction is derivative. In determining it, dealers must conjecture the demand that their clients will direct their way. That demand will be decreasing in non-Boston supply. Boston dealers’ own demand, then, will be decreasing in their estimates of Gloucester supply. The apparent high degree of structural integration of the two ports would suggest that the Boston price, and so the Gloucester price as well, would be nearly as responsive to Gloucester landings as to its own. But this is not the case.

What aspects of the different trade mechanisms might be responsible for Boston dealers taking so little account of Gloucester landings? There are two possible answers. Incomplete observability of Gloucester landings at the auction is one. The catch of each boat landed in Boston is listed on a chalkboard in the auction room. What has been landed and what will be landed in Gloucester that day can only be known from word of mouth, from those who have unloaded or seen boats unloaded there, or overheard some radio conversation. As it is reasonable to suppose that all of the catch at Boston is known, one infers that only about one-third of (the change in Gloucester) trades is observed. So trade mechanisms affect price responsiveness to supply through the observability of trades.

Alternatively, landings in Gloucester might be fully observable at the auction, yet irrelevant to traders there. That supply may not be available to the end-users that the Boston buyers trade with. As is discussed in Section 1.2, there are substantial supply assurance understandings between dealers (those who purchase from the vessels) and their clients further downstream. Those understandings may be so strong that in the short run of a single day, the supply of the two markets may be effectively unintegrated. On the other hand, end-users hold a portfolio of dealers, which may very well

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\(^5\)This is according to the testimony of a Gloucester processor. Georgiana and Hogan (1986) cite a figure of 5 cents a pound (1979) for transportation from New Bedford to New York City.
include dealers in both ports, so that fish landed at different ports might co-mingle along the supply chain and may even end up lying side by side, open mouthed, in a stall at New York City’s Fulton Fish Market. If end-users switch between dealers on the margin, even with substantial supply assurance agreements, Gloucester landings will still matter to bidders in Boston.

The normative and policy implications of these two aspects are quite different. The non-observability of market-relevant trades decreases the efficiency of the allocation of the product; gathering and dissemination information on the supply (and demand) of those trades would improve the allocation of the market. In the second case, buyer and seller pairs’ withdrawal from the market might impose a negative externality on the market, but it is that withdrawal that is the source of the problem and not the non-responsiveness of price.

Whichever of these two explanations is true, however, the non-responsiveness of the auction price to landings in a port so closely tied to it suggests a general principle: that prices in centralized exchanges fail to fully reflect variations in supply traded under bilateral relationships.

The third observation, that Gloucester is less responsive to both sources of supply than Boston is, will receive less attention in what follows. Revenue smoothing, as part of a long term relationship, is a likely explanation. The variance in the value of the landed cod in Gloucester would be 14 percent greater, were Gloucester vessels to land the same quantity but be paid the Boston price instead of the Gloucester price. Obviously, it would be greater still if there were to be a supply response to the more variable price. Vessel owners, who face typical monthly mortgage payments between $6,000 to $8,000 (NEMFC) and as high as $10,000 (Collins 1994), would benefit from this revenue smoothing if they face borrowing constraints.

The interesting question may not be why the Gloucester price is relatively unresponsive to market conditions, but why it reacts to them at all. After all, since trades in Gloucester takes place within the confines of long-term relationship, one shouldn’t have to rely on current prices to clear the market. The answer, of course, is that loyalty to the relationship is unenforceable. Because the rules that govern the relationship between vessel and dealer are not enforceable in court, the actual terms of trade will reflect opportunities outside of the relationship, whether through renegotiation or because the

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6One informant claimed that the typical wholesaler trades with twenty dealers. To my knowledge, no dealer operates in both ports.

7The 14 percent increase is true both for the standard deviation calculated over the entire sample period, and once corrected for monthly means.
The rest of the paper provides a fuller description of the industry, and then both lays out and defends the evidence summarized above. Section 1.2 describes the New England fishing industry and the trade mechanisms used in the ports of Gloucester and Boston. Section 1.3 provides the methodology and statistical evidence, not only for code, but for the other major groundfish species landed in New England ports as well. Section 1.4 provides a fuller discussion of pricing in Gloucester, and considers competing statistical and economic interpretations for our finds: differences in the coverage ratio of the landings in the two ports, the relative timing of sales in Gloucester and Boston, and collusion in Gloucester. In considering (and rejecting) the latter two interpretations, the behaviour of prices in a third port, that of Portland, Maine, will prove useful. It will be shown that the price in Portland is more responsive to changes in Boston landings than to changes in Gloucester landings. Section 1.5 concludes the paper.

1.2 The New England fishing industry

About a thousand boats landed fresh fish in New England during the period of this study. They sold that fish by various means (auctions in New Bedford and Boston, MA, and since 1986, Portland, ME; consignment in Point Judith, RI; bilateral trades in Gloucester, MA) to “dealers”, who are the first buyers, who may either process (i.e., fillet) it themselves, sell it to processors or other wholesalers, or ship it whole to end-users (restaurants, stores and institutional buyers), whether directly or through Fulton Fish Market, which is the wholesale market in New York City. On a daily basis, this industry is little affected by the frozen fish industry, both because the technology for producing frozen fish blocks (which involves huge, almost exclusively foreign factory ships which freeze fish at sea) differs so much from that for fresh fillets, and because a perceived quality difference generates a substantial premium for fresh over frozen, thus making the freezing of freshly landed fish rarely profitable (Georgiana and Dirlam 1982, and Georgiana, Dirlam and Townsend 1993).

Whatever trade mechanism is in place at the ex-vessel level, it must solve a difficult allocation problem every day. First, both the supply and the species composition of that supply varies dramatically from day to day.

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8See Klein (1993), and Baker, Gibbons and Murphy (2001).
9See Graddy (1995) and Chapter 3 for a description of the Fulton Fish market.
For example, the standard deviation of daily changes in the quantity of cod landed in Gloucester is approximately equal to the mean daily quantity landed. Second, the allocation of fish among the dealers must be done rather quickly. Fish spoils – it is no accident that Marshall chose this good to illustrate his “market day” – and dealers need time to contact their buyers further down the distribution chain to see what demand is there. Third, end-users’ typically exhibit very inelastic demand in the short run; both restaurants and supermarkets must set price, whether in menus or advertisements, before demand is realized. This generates the classic supply assurance need between end-users and dealers, who inherit the inelastic demands of their clients.

Boston and Gloucester embodied two different approaches to solving the allocation problem at the ex-vessel stage. In Boston, all dealers gather together at the New England Fish Exchange building every weekday morning at 7:00 a.m. to bid on that day’s landings in simultaneous oral, ascending auctions for each boat’s catch of each species. The quantity brought to market is made known to all participants before bidding begins. There is a price for the entire catch of “market cod” of the *Jules et Jim*, another price for the pollock catch of the same boat, and a third price for “market cod” of the *Dante Alighieri*. At any point in the process, a buyer can bid by raising the price on any species and boat pair. The bidding is typically concluded in an hour’s time. The average price, by species and cull, is subsequently disseminated over the radio. Thirty-three boats landed in Boston in 1991 (NEFMC, 1993). In the early 1980s, which is the early part of our sample, thirty to forty firms purchased at the auction; by 1993-4, just after the sample period, the number of firms had fallen to about eighteen.

In contrast, buyers in Gloucester had long-term, non-contractual rela-

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The following is one dealer’s description of his allocation of his product among his clients:

“One client likes large cod and market cod, another likes market cod and cod scrod, another client likes a little bit of pollock, and it doesn’t matter what kind of cod. So it all depends on what we have, and we have to decide with what we have, who we would target first, and we would call them first, and give them the first shot, and then if that doesn’t fly, then we call somebody else, and then if we really have to, but we really haven’t had to, because we do have a pretty good clientele, we break it up somehow, and maybe have to go to two different places. But worst comes to worse, if no one could agree to take it all, we could get rid of it all in one place in [a major city], ..., and he wouldn’t be too happy to hear about all the other customers. Well, he knows, but if you don’t rub their nose in it, it’s not a problem.” (Personal conversation, 1992.)

This description of the market, and the dealer’s function in it, is reminiscent of Carlton (1991), which views firms as allocating their product among their buyers, according to their knowledge of their buyers’ demands.
tionships with vessels. These bilateral relationships lasted about a year
during the same period, and were apparently somewhat weaker in the later
part than in the earlier. They involved not only a commitment to trade
with one's regular partner, but also the dealer's provision of certain inputs,
such as ice, to the vessel. Traders are dispersed along the waterfront, and
prices are determined by independent bargaining dispersed in time over the
course of the morning. There is no organized announcement of landings.
Two hundred and four boats landed in Gloucester in 1991, though only
half landed groundfish. In the early part of the 1980s, there were perhaps
twelve buyers. Ten years later, there were about six or seven buyers, the
rest having left Gloucester or the industry in the intervening years. What
are the relative advantages of these two trading mechanisms? The principle
disadvantage of a long-term relationship is the arbitrariness it imparts to
the allocation of fish to dealer. Vessels' fishing efforts will presumably be
directed to their dealers' preferred portfolios, but given the inherent ran-
domness of the vessel's catch and transitory shifts in the demand of the
dealer's clients, any given day's match of catch to dealer is likely to be far
from efficient. The consequence of a worse allocation at this stage is ei-
ther greater inefficiency at the end-user stage, or costly actions by dealers
to improve efficiency further upstream. The latter requires either a greater
array of clients for each dealer (who overlap across dealers) or trades among
dealers themselves Wilson (1980).

There may be several advantages to long term relationships. Wilson
(1980) has argued that such relationships in ex-vessel trades thwart oppor-
tunistic behavior by dealers whose information about demand conditions and
supply conditions elsewhere is superior to sellers'. But that reason seems
more appropriate to the small ports of Maine that may boast only a single
dealer than to a large port like Gloucester. Bilateral trade does economize
on middlemen, of which the auction is one; but the dealer in Gloucester is
typically a middleman himself, and not a processor, as only a fraction of
fish landed in Gloucester is, in fact, processed there. Another possible ad-
vantage to long-term relationships is that vessels can inform their dealers of
the size and composition of their landings earlier, and thus provide dealers
with more time in which to allocate their product among their clients.11 I
suspect that this lead time is the most important benefit of the long-term
relationship. Thus a system of long-term relationships reduces the dealer's

11The argument is reminiscent of Arrow (1975), where firms purchase their suppliers so
as to gain early information on upstream supply conditions, and thus improve investment
decisions.
direct allocation costs at the expense of a less efficient allocation among dealers themselves.  

The advantage to the auction mechanism is, of course, the better allocation of fish among the dealers. Its disadvantage is the need to agglomerate trades in time and space. The latter is not obviated by electronic trading, given that buyers need to inspect the fish quality (if not before, as in display auctions, then right after the trade, as in Boston). Time and space agglomeration is mitigated by the economies of scale, such as specialized unloaders.

However much these explanations might illuminate the relative advantages of long-term relationships over centralized trade, none explain why the auction is in Boston and not Gloucester. If we are to attribute the impotency of Gloucester landings to the differing trade mechanisms, we must be sure that there is no factor that makes Boston suitable for an auction, and Gloucester not, and which is also responsible for the relative inability of Gloucester landings to move prices. Understanding why the auction is in Boston and not in Gloucester should help us in that.

One would have expected the opposite. Fish auctions are found only in major ports, for the obvious reason that the fixed costs involved in establishing a formal, centralized marketplace require a large volume of trade. Boston is, indeed, a major port, but Gloucester is a larger one. As Table 1.1 shows, Gloucester has landed more groundfish than Boston since the early 1970s, and more of all species combined since World War II. During the sample period, it landed between six to nine times as much fish as Boston did, and at least fifty percent more groundfish than is traded at the auction (the auction trades almost nothing other than groundfish.)

The answer lies in the combined effects of history and sunk investments in infrastructure. Trading exchanges have a network good aspect to them, leading to multiple equilibria, and so providing an opening for history to determine the outcome. Empirically, Carlton (1991) has shown very clearly, the role of inertia on the continuance of organized trading places. So it is noteworthy that Gloucester was not always larger than Boston. In 1908,  

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12Lead time will in some cases be no more than an hour or two, because to protect their private information on the location of the fish (which Wilson (1990) has described) vessels will sometimes wait until they are near to shore to contact the dealer and inform him of the catch (personal conversation with dealer, 1992).

13It is also possible that the equilibrium system of mechanisms is for there to be an auction in one port, and bilateral trading in another, but with an arbitrary assignment of port to mechanism.

14See, for example, Economides and Siow and Pagano (1989a, 1989b).
the year in which the Boston auction was established (White 1954; German 1982, page 4), groundfish landings in Boston slightly exceeded Gloucester landings. The history of the ensuing years is instructive. Over the next 25 years, Gloucester declined while Boston prospered, the latter arguably because of the auction, or more specifically, the million dollar state financed pier that was constructed in 1914 to serve the auction. Gloucester recovered somewhat in the early 1930s with the development of the market for redfish, which were located somewhat closer to Gloucester. Still, on the eve of World War II, Boston was landing four times as much groundfish as Gloucester. With the war, however, came competing demands on the Boston port. Boston landings in 1942 were only two-thirds, and in 1943, only half, of 1941 levels.

In 1944, Gloucester surpassed Boston. Significantly, that same year saw the establishment in Gloucester of a selling room - an auction by the Atlantic Seamens Union. Although one informant of mine claimed that the auction closed within a year, it was obviously still operating when White wrote his dissertation in the early 1950s. It apparently closed soon after, as Doeringer, Terkla and Moss (1986) claim that the auction operated in the late 1940s and early 1950s.

The reason for the demise of the Gloucester auction is unclear. The two month strike by the union in 1953 may have played a role. Another factor might have been the lack of any supporting investment in infrastructure. Yet a third factor might have been the ease of defection from the exchanges. With port land relatively cheap in Gloucester, it would have been easy to have re-established the dealer-vessel bilateral relationship, a much more difficult proposition in Boston, especially after the war. Ironically, the same force that robbed Boston of its volume of landings may have also supported the auction equilibrium there. Thus the presence of the

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15 The 1908 data are county level data. The country description suggests that whereas there were several other smaller ports in Essex county, where Gloucester is located, Suffolk county only had Boston, which indicates that the difference in groundfish landings at the two ports was somewhat greater than the numbers indicate. The numbers for the remaining years are all calculated at the port level.

16 However, Doeringer, Terkla and Moss (1986) claim that the union operated a “selling room” in Gloucester in the late 1940s and early 1950s. In 1941, the Atlantic Fishermen’s Union had established an auction in New Bedford, and, until the summer of 1994, that port has not been without an auction since (though control of it has changed hands twice). In the early 1990s, there was talk of establishing an auction in Gloucester, but no auction was established. Aside from the usual difficulties of establishing centralized trading places, the effort faced the closures of vast fishing areas mandated by federal management policy, in response to the depletion of the New England groundfish stocks, the consequences of which are evident from the landings figures in Table 1.5.
auction in Boston and not Gloucester would appear to be the result of a number of historical events unrelated to other aspects of price determination. Indeed, that Boston is the smaller port makes the results of this paper all the more striking; this is an example of the tail wagging the dog.

1.3 The evidence

For most industries, determining whether a supply shift in one market segment has a greater effect on price than would an equivalent supply shift in another segment would be a difficult task. But the fishing industry boasts daily and vigorous supply shocks, which allow us to check the hypothesis in a very simple way: does the price in Gloucester respond more to a one pound increase in Boston landings than Gloucester landings?

Formulating the hypothesis that way suggests estimating the following simple regression

\[ p_t = a_0 + a_B B_t + a_G G_t + \epsilon_t \]  

(1.1)

where \( p_t \) denotes the price in Gloucester, and \( B_t \) and \( G_t \) denote the quantities landed in each of the two ports. Under the null hypothesis of perfect competition, Eq. 1.1 has the interpretation of an inverse excess demand curve. The error term, \( \epsilon_t \), represents deviations in inverse excess demand, and includes both variations in demand by end-users, such as restaurants and supermarkets, own-species supply elsewhere, such as landings in other New England ports and fresh imports from Canada, as well as landings of other species and variations of supply in competing non-fish food products.

My interest is in the relative responsiveness of prices to the daily shocks to supply in each port, i.e., \( a_G/a_B \). Ordinary least squares estimation of Eq. 1.1 would confound that pricing responsiveness with the supply responsiveness of the Gloucester and Boston groundfish vessels, who, over time, may enter or exit the industry, or shift across species, in response to any of the omitted excess demand factors listed above. Should the supply response to these omitted factors be the same in each port and so impart the same bias to the coefficient on Gloucester supply as to that on Boston supply, the result would be to bias the ratio of the coefficients to one. The test for the null hypothesis of equal responsiveness would remain valid, but it would be

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17 What is landed at a port and what is traded there ex-vessel can differ now that trucking from the vessel itself has become more common in the industry. However, a very small fraction of landings are immediately trucked to or out of Gloucester, and none in or out of Boston.
low power, and of course the ratio of interest would be unrecoverable. Furthermore, the induced response need not be equal. On the one hand, with the mean Gloucester supply larger than Boston’s, we would expect the level response also to be greater. On the other hand, as the Boston labour market is many times larger than that of Gloucester, we might expect entry and exit in the Boston port to be greater. With these two effects, irrespective of which dominates, even the test of the null hypothesis would be invalid.

My solution to this endogeneity problem takes advantage of the nature of production and the timing of price determination in the industry. Almost all the volume landed at the two ports comes from “trip” boats that go out to sea for five to ten days (Georgiana, Dirlam and Wang 1991) and require a day’s return from the fishing grounds to the port. Only once the vessel is in port is the price determined, rather by auction or bilateral negotiation. Consequently, while supply can respond to higher prices within a period as short as a week or two, it can not do so on the same day as the price shock.

Thus by controlling for the predictable component of excess demand, and so isolating the unpredictable innovation in demand, the parameters in Eq. 1.1 can be consistently estimated.

Formally, I model the serial correlation of the error term as a first order autocorrelation process, and add the following conditions to Eq. 1.1

\[ \epsilon_t = \alpha \epsilon_{t-1} + u_t \] (1.2)

\[ \text{plim}_{s \leq t} Q_s u_t = 0, \quad Q = B, G \]

which, as suggested by Durbin (Harvey, 1991, p.194), allows Eq. 1.1 to be rewritten as

\[ p_t = a_0 + \alpha p_{t-1} + a_B \Delta_a B_t + a_G \Delta_a G_t + u_t \] (1.3)

where \( \Delta_a = 1 - \alpha L \) is the quasi-difference operator. The parameters \( \alpha \), \( a_B \) and \( a_G \) may be estimated by nonlinear least squares applied to Eq. 1.3.

This approach, of course, assumes that the fishermen cannot anticipate the innovation \( u_t \). That seems reasonable to me, as any information on excess demand is likely to be known by the dealers on shore and so reflected in prior days prices (i.e., \( \epsilon_t, s < t \)). Even if they could anticipate it, they would have to be able to do so several days beforehand for the information to be useful. First, given the day required to return home, a one day lead would be of no use. Second, there is little opportunity to profitably time the return to port the fish - leaving early sacrifices quantity, while leaving
later risks spoilage and wastes the crew’s time. Fishing is not that flexible. As Binkley (2002, p. 46) writes, “Deep sea fishing is actually hunting at sea. There is no guarantee that fish will be available at any particular time, or that they will remain available in any particular area. Therefore, once a crew finds fish and begins to catch them, they must continue to harvest and process the catch until there are no more fish.” Or capacity is reached.

In practice, this quasi-differencing approach requires large day to day, and cross port, variation in supply. Such variation clearly exists, due to weather conditions (although because the vessels fish in the same areas, most of that will be common across ports), as well as the randomness of the total volume and species composition of individual boats’ catch, and the timing of trips, including shipping mishaps that force boats to return to shore with a less than full catch.

In principle, there may be a second endogeneity problem. If the Gloucester price is abnormally high (say, because demand of Gloucester buyers is abnormally high), it may induce boats that would normally land in Boston to land in Gloucester instead. The effect of such behavior on OLS estimates of Eq. 1.1 will be to increase the coefficient on the own-port (decrease its absolute value) relative to coefficients on quantity landed in other ports.

This bias is likely to be quite small, for the opportunity for vessels to shift between the two ports in the short run is quite limited. Landing at a port other than one’s own requires either that the crew be deprived of shore leave, or that both fuel and time be expended in traveling to the home port; traveling by sea is much more difficult than traveling by land. Fishermen’s time on shore between trips in the busy season is already quite short, compressed and thus very stressful, as several anthropological studies of fishermen’s families have described.18

For Gloucester based boats, landing elsewhere has the additional disadvantage of potentially jeopardizing the long-term relationship with the dealer. As for, Boston boats landing in Gloucester, they do not have the benefit of a long-term relationship to protect them from the dealer’s opportunistic behavior once the fish is unloaded. Also, until 1993, which is after our sample period, there was no public docking area in that port. Permanently switching ports is especially costly; it requires either a new crew, or that the existing crew relocates. As many of the crews are kinship based, the former would be especially difficult to do. But shifting among ports does occur, both in the short and long term, and so this endogeneity problem

18Examples include and Brinkley’s (2002) study of fishermen families in Atlantic Canada, especially page 53.
needs and will be addressed below.

All data are derived from the National Marine Fisheries Service’s (NMFS) Landings File, 1982-1992. NMFS attempts to conduct a complete census of U.S. fish landings. The attempted census uses buyer reports, and is more successful in some ports than others. (The implications of the differential coverage rate in Gloucester and Boston are examined in Section 1.4 and the Appendix.) This program was voluntary over the sample period. No quotas were in force for any of these species during the period. The Landings File is the compilation of weigh-out slips filled out by each buyer of fish from a vessel. For quantities, I use the total volume landed in each of the two ports. For price, I use the (unweighted) mean price of that port’s landings, where price is the ratio of value to volume, deflated by the monthly CPI.

I consider nine species: cod, cusk, yellowtail flounder, American flounder, haddock, hake, redfish, pollock, and wolfish. These species were chosen because, as Table 1.2 shows, Boston lands very little of any other species. I include all days on which there are positive quantities of the chosen species and cull landed on that day and the previous day in each of the two ports. Because the Boston auction was usually closed on weekends during this period, most of the days in the sample fall between Tuesday and Friday.

Table 1.3 shows the summary statistics. Cod sells, on average, for 60 cents a pound (in 1982-84 dollars), and in revenue terms is the dominant species. Twenty-one thousands pounds a day are landed, on average (when any are landed), with about two-thirds of that landed in Gloucester. Of groundfish, only Pollock has a greater volume (at about 28,000 pounds), but at half the price. At Yellowtail Large American flounder, and large haddock are more expensive (large haddock almost twice as much), but much less of each is landed. All the other major groundfish species sell for less than cod, at prices that range between thirty-one to thirty-eight cents.

Table 1.4 presents ordinary least squares estimates of Eq. 1.1. The top panel shows regressions with the Gloucester price as the dependent variable, the bottom with that of Boston. There is no systematic pattern to the coefficients here. For some species, the coefficients on the landings in the two ports are quite close, as for cod in Gloucester, and Pollock and Wolfish in both ports. For others, Cod in Boston, and Cusk, Large American Flounder and Haddock in both ports, Boston landings have a greater effect than Gloucester landings on the price. For the remaining species, it is Gloucester landings that have the greater effect. In all cases, the Durbin-Watson statistic is very large, indicating a very high degree of autocorrelation of the error term and/or misspecification. Likewise, when yearly dummies are included, the set are significant at the two percent, and typically much lower, level.
Table 1.4 presents estimates of Eq. 1.3. Without exception, and for both the Gloucester price and the Boston price, the coefficient on the quasi-change in Boston quantity is significantly more negative than the coefficient on the quasi-change in Gloucester quantity. For four of the nine species – Yellowtail Flounder, Unclassified Redfish, Drawn Pollock, and Wolifish – one cannot even reject the hypothesis that Gloucester quantity has no effect on either Gloucester or Boston price. When yearly dummies are included, the $F$-statistic for joint exclusion is highly insignificant, with $p$-values of at least 65 percent. The estimates in Table 1.5 repeat the three basic facts.

The large positive serial correlation in the demand error is not surprising. First, the high frequency of the data of itself suggests a large positive serial correlation. Second, opportunities to inventory the fish for a day or two exist at all stages of the industry, including the processor, wholesaler and end-user stage. That implies some degree of demand substitutability between any two days. Third, the error will reflect supply at other ports, both in New England and elsewhere, which, especially because of seasonal effects, is serially correlated.

To make sure that our findings do not result from functional misspecification, I consider an alternative specification in which the inverse demand curve is linear in the log of quantity:

$$p_t = a_0 + \alpha p_{t-1} + a_B \Delta \alpha \ln[B_t + \beta G_t] + u_t$$

(1.4)

$\beta$ measures the impact of Gloucester landings relative to Boston landings.

Table 1.6 presents nonlinear least squares of Eq. 1.4. With the exception of one species, $\beta$ is always estimated to be positive but less than one. The coefficient on the log of quantity is, again with one exception, always negative and typically twice as large when the Boston price is the dependant variable than when the Gloucester price is. The abnormal results are for Yellowtail Flounder and seem to be due to local non-identification. The estimated value of $\beta$ is much less constant across the species than the ratio of coefficients presented in the previous table. Nonetheless, the three basic findings with which this paper began are clearly robust to the choice between the linear and the linear-log inverse demand curves.

Table 1.7 examines two additional extensions to the empirical analysis for the most important species, cod. The first two columns repeat the estimates for that species from Table 1.5. The following two columns add the lagged one day landings to the inverse demand curve, so that, taking into account first order autocorrelation in the error term, it presents the regression of price on lagged price and the quasi-differenced landings for the day of sale and
the preceding day. The same basic pattern of greater relative sensitivity to Boston than to Gloucester landings in both ports, and overall greater sensitivity in Boston than in Gloucester is evident not only in the concurrent day landing coefficients, but also in the coefficients on the lagged landings. The magnitude of the lagged effects is about a third to half that of the concurrent effects.

Table 1.7 also shows the effect of landings in these two ports on price in a third port. How price in some third port responds to landings in Boston and Gloucester can help discriminate among the various interpretations of our three basic findings. How we evaluate the price response will, of course, depend on the pricing mechanism in the third port. New Bedford, MA and Portland, ME are the two other large New England ports. Unfortunately, in neither of them has a single price mechanism been used to the exclusion of all others over our sample period. New Bedford has had an auction since 1941, but not all transactions in New Bedford are conducted through the auction. I have no data on the share of auction transactions during the sample period, but in 1994, the auction’s share of all landings was only one-third and in September 1994, the auction closed down temporarily. Portland’s auction was established only in 1986, and though it struggled through its first few years, by 1994 it commanded a volume equal to all of Portland landings. Only about half of Portland landings actually traded at the auction, however, with the rest of the volume of the auction being trucked in from other Maine ports or Canada. Non-auction transactions in both ports operate in a similar manner to Gloucester.

Of the two, Portland is more useful. Portland is much more distant from Gloucester and Boston than the two are from each other, and, being north of Gloucester, is somewhat closer to that port than to Boston. It is thus reasonable to suppose that the degree of structural integration between that port and either of the other two is essentially the same. Also, the Portland auction data has been made available to me.

Table 1.7 documents the behavior of the Portland price, for cod. Column (5) shows the regression of the Portland price on its one day lag, and the quasi-differenced landings in all three ports. Strikingly, Portland is, like the other ports, three times as sensitive to Boston landings as to landings in Gloucester. It is interesting to separate out the auction from the non-auction trades in Portland. To this end, column (6) is restricted to the 1982-May 1986 period, whereas column (7) is restricted to the June 1986-1992 period, and uses the average price at the Portland auction. At this

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19 The NMFS’ data (described in Section 1.3) do not discriminate between auction and non-auction landings.
point, the decrease in the number of observations and the thinness of the Portland auction in its early years takes its toll on the standard errors, but the general pattern remains the same both on and off auction: Boston supply has a greater impact on price than does Gloucester supply.

1.4 Pricing in Gloucester

Because the two ports do not operate in isolation, the behavior of prices in any one port depends not only on the mechanism of trade there but on the mechanism operating in the other port as well. Fortunately, our task is considerably eased by the mechanism type in Boston, as we can reasonably approximate the auction price mechanism by the competitive mechanism. This is not to deny the presence of strategic opportunities to misrepresent one’s true value at auctions; however, Rustichini, Satterthwaite and Williams (1994) and Cripps and Swinkels (2006) have shown that such opportunities are very small at double auctions (of which the simultaneous auction in Boston must be a close cousin) with only a few participants.

About the nature of bargaining in Gloucester, we know much less. The testimony of market participants is that the Gloucester price is “set in Boston”. In practice, this convention takes the form of quoting the price as a discount off the known, or perhaps not yet known, Boston price. However, the mere existence of this convention does not reveal how much freedom remains in the setting of the Gloucester price. In principle, pricing with reference to the Boston price need not constrain the Gloucester price at all, as the discount might vary freely, leaving the pricing convention essentially meaningless. However, that for all species the relative effect on price of Gloucester and Boston supply does not differ much by port suggests that the Gloucester price is, indeed, mimicking the Boston price, though also smoothing it.

Although transactions in Gloucester are part of long-term relationships, their prices nonetheless reflect current market conditions, if not in Gloucester than at least in Boston. The reason why long-term partners, who, after all, have removed themselves from the market, might, nevertheless, choose to tie their prices to it is familiar from the literature on specific investments and implicit or legally unenforceable contracts. Because the rules that govern the relationship between vessel and dealer are not enforceable nonauction trades. Columns (5) and (6) use average prices derived from the NMFS data. Column (7) uses average prices from the Portland auction’s own records. In all columns, the definition of the Portland supply is the NMFS’ figures on the catch landed at Portland.
in court, the actual terms of trade will reflect opportunities outside of the relationship, whether through renegotiation or because the rules are structured beforehand so as to ensure voluntary compliance. It might seem that, if there is any significant value in the relationship, the prospect of an improvement in one trip’s revenue or outlays would be insufficient to tempt either side to trade outside of it. But given the high autocorrelation in market prices, which is inherent in the seasonality of excess demand, any discrepancy between a stable price within the relationship and the market price is likely to persist for several trips. For example, were prices held constant throughout the year near the yearly market average, then sellers might find it advantageous to dissolve the relationship near the beginning of the spring; buyers would face a similar incentive in the fall. Prices within a relationship will thus inevitably reflect market conditions. Indexing prices to a spot market to begin with is an obvious way to formalize this within an existing agreement.

Viewing Gloucester prices in this way suggests a possible explanation for the last of our three findings from Tables 1.5, 1.6 and 1.7: that the Gloucester price is less sensitive to supply shocks from either port than is the auction price. Non-cooperative bargaining theory predicts that a negotiated price will reflect either a surplus sharing rule (the Nash bargaining solution), or the outside option of one of the bargainers. The surplus sharing rule would predict prices that are less responsive within than without bilateral relationships, if an increase in the market price increases the surplus by an amount no greater than one. That condition is satisfied if we interpret the threat point in the Nash solution as the value of abandoning the partner for a single trip’s transaction only and then assume some positive probability that the vessel will fail to find a substitute partner for that period.

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20The best known example is the indexation of long-term coal contracts to the spot market (Joskow 1990). Spot transactions in the coal market typically are for a month’s worth of delivery; the average duration in Joskow’s sample of long-term contracts is thirteen years. Since a vessel is typically out at sea for anywhere between ten days to two weeks, and long-term relationships currently last about a year (though were perhaps somewhat longer in the 1980s), the value of a spot transaction as a proportion of the value of all transactions in the relationship is about three times as great in the ex-vessel market as in the coal market.

21See MacLeod and Malcomson (199?) for a model in which trade is simultaneous with the bargaining game, and the threat point represents non-trade with the partner. It is natural to interpret the outside option as the value of a permanent dissolution of the relationship.

22Let \( p \) define the market price, \( p + k \) and \( p + k' \) the return to the dealer of a sale to his client when the catch originates from his regular partner and from some other vessel, respectively, and \( a_B \) (\( a_S \)) the probability that another vessel (dealer) from which to buy
Of course, the true alternative is to trade elsewhere in Gloucester, not Boston. But to gather information on supply and demand available in decentralized markets requires one to canvass other market participants; that activity is time-consuming. Quoting prices from another port conserves on that cost tremendously, at the cost of the use of an inappropriate representation of the outside opportunity. That cost will be small when the degree of structural integration of the two ports is great. Also, as long as others in Gloucester are “pricing by Boston”, Boston will represent the outside option.

1.4.1 Other explanations

There are three other possible interpretations of the differential measured effect on Gloucester price of contemporaneous supply: the variable coverage ratio of Gloucester landings, the relative timing of landings in the two ports, and dealer collusion in Gloucester. I consider each in turn.

Unrecorded landings in Gloucester

Variability in the coverage ratio in Gloucester is an obvious explanation for the apparent impotency of Gloucester trades in moving price in either port. All Boston trades occur through the auction, and, consequently, are recorded in the NMFS file. In contrast, the port agents in Gloucester estimate that they miss between 5 to 15 percent of any given day’s landings, and about 10 percent on average. This variation in the coverage ratio generates a nonlinear errors-in-variable bias.

As the Appendix shows, the probability limit of the NLS estimator of \( a_G \) in 1.3 is approximately equal to \( a_G(\lambda/\mu) \) where \( \mu \) is the mean coverage rate, and \( \lambda \) is the (rescaled) signal to total variance ratio, so that \( \lambda/\mu \) is the regression of the change in total Gloucester landings on measured Gloucester landings.\(^{23}\) The bias from the missing landings cuts both ways. On the one hand, because measured landings are a fraction of total landings, there will be a tendency for \( a_G \) to be biased away from zero in order to adjust for scale. On the other hand, daily variations in the extent of coverage will

(23) The appendix shows that the correlation between daily changes in landings in Gloucester and Boston is sufficiently small that the correction for the presence of the Boston landings as a regressor is negligible.

Alternatively, one might assume that the vessel can always find a partner, but with delay that causes quality deterioration, with a corresponding proportional decrease in price.
bias $a_G$ towards zero, and to the extent that daily changes in the two ports are positively correlated, $a_B$ away from zero, in the manner of the classical errors-in-variables problem. As it turns out, the scale effect dominates the errors-in-variable effects. The algebra is relegated to the appendix, but the reasoning is simple. The variance of the change in the coverage ratio is too small to explain the results. The variance of the level of the coverage ratio is bounded by the lesser of the square of the distance from the minimum or maximum to the mean, which, if the port agents are to be believed, is $(.95 - .9)^2 = (.85 - .9)^2 = .0025$, so that the variance of the change is at most twice that, assuming that the autocorrelation in the coverage ratio is nonnegative. This implies that $\lambda \approx 1$.

The assumption that the coverage ratio is independent of total landings is reasonable if we think of the probability that a boat’s catch fails to be recorded on any given day as essentially random (because the weigh-out slip is lost, for instance). It is less reasonable to the extent that the unrecorded landings represent a set of boats that are rarely covered (such as boats that predominately deal in cash, or sell to very small dealers). However, the Appendix shows that here, too, the resulting bias leads to an underestimate of the true differential.

Timing of trades

The next competing explanation relies on Boston’s supply arriving earlier and in a narrower time span than Gloucester’s. Recall that the Boston auction begins at 7:00 am and ends an hour later. It would be reasonable to suppose, then, that the price of the last trade of the day in Gloucester incorporates more information about the total quantity landed there that day than does the first trade’s price; both incorporate the whole of Boston’s supply, since that is known relatively early on in the day. If so, then as the Gloucester price is the mean of all Gloucester prices throughout the day, Gloucester supply will be seen to affect Gloucester price less than Boston supply does.

Though the relative timing argument can explain the first observation, it fails to explain various other empirical regularities in the data. If timing is the sole explanation, than Gloucester prices should incorporate much more of Gloucester trades than Boston does, implying the ratio $a_G/a_B$ should be larger in Gloucester than in Boston. To see this, let $m$ be the fraction of Gloucester landings that occur before the auction, and assume the two ports

\footnote{Unfortunately, the time of a given vessel’s landing in Gloucester is unknown.}
are always in the arbitrage regime. If prices incorporate only the supply that
has been landed already that day, then (minus) the mean Gloucester price
will be \( \int_0^{mG} x dx + [\int_{mG}^{G} x dx + (1 - m)B] \), and (minus) the Boston price will be \( B + mG \). Under
this scenario, the ratio \( a_G/a_B \) will be \( \frac{1}{2(1 - m)} \) and \( m \) in Gloucester and Boston,
respectively, so that the supply responsiveness ratio of the Gloucester price
would be at least twice that of Bostons.\(^{25}\)

The lagged effects estimated in Table 1.7 are also inconsistent with the
timing explanation. Since by date \( t \) all of \( B_{t-1} \) and \( G_{t-1} \) will have been
landed and traded, the relative timing argument predicts that the two coef-
ficients equal each other, if the two markets are structurally integrated, or if
not, \( a_{G1} \) should exceed \( a_{B1} \) in the Gloucester price equation in magnitude.
The opposite, however, is true.

Finally, and most convincingly, the behaviour of the Portland price is
inconsistent with the timing explanation. As the Portland auction takes
place rather late in the day, at one in the afternoon, when most if not all
of the Gloucester vessels would have landed and sold their fish, the timing
explanation would predict that its price should be as responsive to Glouces-
ter as to Boston supply. Yet the differential effect is clearly evident in the
Portland price.

Collusion

The third explanation relies on collusion.\(^{26}\) Perhaps, the dealers in Glouces-
ter are more effective colluders in their trades with vessels than their coun-
terparts in Boston. Indeed, the relative concentration of buyers and sellers
in the two ports suggest that Gloucester dealers would find collusion easier.
Of course, the number of dealers is, in part, a consequence of the trading
institutions themselves. One doesn’t need a pier to be a dealer in Boston.\(^{27}\)

By itself, collusion cannot explain the empirical results. A perfectly col-
lusive equilibrium would not entail a price that is more responsive to own
supply than to Boston supply. However, Gloucester’s dealers might find the
Boston price to be a convenient focal point. Under this interpretation, the
pricing convention serves not to solve the bilateral monopoly problem, but
to aid dealer collusion. Collusion in an environment in which supply shifts

\(^{25}\)The difference would be even greater if the markets were not wholly integrated.
\(^{26}\)Although accusations of price-fixing in purchasing have been leveled against Glouces-
ter dealers, they have never been proven. An indictment against dealers in New Bedford,
MA, was handed down in the mid-1990s (Commercial Fisheries News).
\(^{27}\)Also, by an antitrust decree from 1919, the auction in Boston is open to all.
so dramatically from day to day and supply assurance is so crucial, as is
the case in the fishing industry, is not an easy task. A successful collu-
sive price, one that would ensure maximal profits such that no firm would
find it individually advantageous to cheat on the agreement, would have to
be continually recalibrated as supply and demand conditions change. How
much easier to rely on an agreement to price according to the publicly an-
nounced price from Boston! There would be a loss to using the Boston price
(or some simple adaptation of it), rather than the optimal collusive price,
but so long as the two markets are sufficiently integrated and competitive
bidding reflects supply and demand conditions, that loss will be small.

A variation on the collusive story is secret price hikes. According to
this view, dealers do not report to the NMFS the true price they offer their
suppliers, for fear of being caught cheating on the collusive agreement by
other dealers. The error in Eq. 1.3, $u_t$, will represent, in part, deviations
of the true from reported price. If the incentive to cheat on the agreement
is highest when supply in Gloucester is lowest, then $u_t$ will be positively
correlated with Gloucester supply, and so will impart an upward bias to the
estimated value of $a_G$.

There are some problems peculiar to the ‘secret price cutting’ version.
To begin with, the NMFS does not publicly announce the individual trans-
action prices. This version of the collusive story also has the unfortunate
implication that the relative supply effect in the Boston equation (which is
understood to reflect the degree of structural integration) is equal to the
relative supply effect in the Gloucester equation (which is understood to
reflect the correlation between price cuts and Gloucester supply).

Both versions of the collusive explanation ultimately fail to explain the
small effect of Gloucester supply on prices in Boston and Portland. In order
to explain the Boston price equation, the collusive story, of either version,
must assume that the two markets are far from fully integrated. Such an
assumption faces a number of difficulties. First, it is inconsistent with what
is known about these markets, as presented in Section 1.2. Second, as we
see from Table 1.7 the Portland price assigns the same relative weight to
Gloucester as does Gloucester.

It needs emphasizing that nothing here precludes the possibility that
dealers in Gloucester may, in fact, collude, only that collusion cannot explain
the empirical regularities I have presented here.
1.5 Conclusion

Fish is not the only good whose transactions are governed by both a centralized exchange and long-term, bilateral relationships. It is merely a convenient good to study, given the nature of its supply shocks. As the studies in Hayenga (1979) point out, many agricultural products, such as sugar,\textsuperscript{28} cheese, butter, eggs, and meats, have a similar trading structure. There, too, the long-term partners trade at a price pegged, formally or informally, to the exchanges price. Indeed, in many cases, the imbalance between the volume on and off the exchange is much more extreme than described here. Less than one percent of the cheese is sold at the National Cheese Exchange, yet the price there governs the bilateral relationships. Sometimes there are no trades at this and other exchanges, and a committee sets the price instead, which the off market trades follow.

For other products, decentralized spot markets take the place of the exchange. In such cases, long-term partners use an average of the spot prices that government or commercial reporting agencies have gathered and disseminated the spot prices. Markets for many fuels, such as coal in the United States, which Joskow (1990) has described, operate in this fashion. Such is the situation for many agricultural products, after technological changes led to the demise of the wholesale exchanges at city terminals (Hayenga 1979). Here, too, the situation can be quite extreme, with all transactions pegged to the reporting price. The central lesion of this paper is that the mechanism of trade matters for the responsiveness of price to supply. It is also reasonable to conclude that the mechanism of trade will matter for the responsiveness of price to demand, as well. Thus when evaluating the effect of an increase in supply or demand, or the volatility of the same, it is essential to know where that demand or supply will be expressed. For example, an increase in demand for American currency if exchanged between corporations and individuals, without bank or market intermediation, will not move the dollar as much as an equivalent increase in demand that is effected at one of the currency exchanges. Likewise, with the emergence of Internet sites that cater to wholesale trades among firms and eBay, we should expect that changes in supply for those goods that were previously traded in many isolated bilateral transactions or small stores would have a much greater change in price than before.

This is not an issue that has received any attention in the theoretical or

\textsuperscript{28}American Sugar Refining Corporation’s three year contract with the Hawaiian Growers’ Association stipulated that price would be transacted at the daily raw sugar price in New York City.
empirical literature. There has been a tremendous amount of work on the implications for the terms of trade and the allocation of goods of the choice of trading mechanisms, and, more recently, some matching empirical work (although most empirical work uses the theory simply to infer bidders’ values). There is also a smaller theoretical literature on the equilibrium choice of trading mechanisms. It is rare, however, for different trading mechanisms to co-exist in equilibrium in such models.\textsuperscript{29} When they do, the consequences for the effects of demand or supply shocks are not examined.

Left unresolved here is which of two aspects of the trading mechanism is responsible for the differential effect on price. Is the source of the lower responsiveness of price to supply shocks within the long-term relationships a lesser observability of those trades or that those buyer and seller pairs have removed themselves from the market, making their demand and supply irrelevant? It will be necessary to repeat the empirical exercise of this paper in industries where the off-exchange transactions are between short-term buyer and seller pairs in order to answer that question.

\textsuperscript{29}See Kranton (1996), Gehrig (1996) and Rust and Hall (2003).


[21] MacLeod and Malcomson (199x).


[26] Peterson, Susan and


Appendix: Unrecorded landings in Gloucester

I - Independent Coverage Ratio

Let $\delta$ denote the coverage ratio, $G$ the recorded landings in Gloucester, and $G^*$ total landings in Gloucester, so that $G = \delta G^*$. Assume that $\delta$ is distributed independently of both $G^*$ and lagged values of itself, and has mean $\mu$ and variance $v$, and that $\alpha = 1$.

We will have need of the following identities:

$$E\delta \Delta \delta = v$$

$$E \Delta \delta \Delta \delta = 2v$$

$$E \Delta G^* \Delta G^* = 2E G^* \Delta G^*$$

as well as the approximation

$$\Delta G \approx \delta \Delta G^* + G^* \Delta \delta$$

The probability limit of the NLS estimator of $a_G$ is

$$\frac{\sigma_{\Delta p \Delta G} \sigma_{\Delta B}^2 - \sigma_{\Delta p \Delta B} \sigma_{\Delta B} \Delta G}{\sigma_{\Delta G}^2 \sigma_{\Delta B}^2 - \sigma_{\Delta B}^4}$$

$$= a_G \frac{\sigma_{\Delta G^* \Delta G} \sigma_{\Delta B}^2 - \sigma_{\Delta G^* \Delta B} \sigma_{\Delta B} \Delta G}{\sigma_{\Delta G}^2 \sigma_{\Delta B}^2 - \sigma_{\Delta B}^4}$$

$$\approx a_G \frac{\frac{\sigma_{\Delta G^* \Delta G}}{\sigma_{\Delta G}^2} - \rho^2}{\mu}$$

$$= a_G \frac{\lambda - \rho^2}{\mu(1 - \rho^2)}$$

where $\rho$ is the correlation between measured daily changes in landings in the two port, and $\lambda \equiv \mu \sigma_{\Delta G \Delta G^*} / \sigma_{\Delta G}^2$. The approximation follows from $\sigma_{\Delta G \Delta B} \approx \sigma_{\Delta G \Delta B} / \mu$. Note that were $\delta$ constant, $\lambda$ would equal one. To calculate $\lambda$, first note that

$$\sigma_{\Delta G \Delta G^*} = \text{Cov}(\delta \Delta G^* + G^* \Delta \delta, \Delta G^*) = \mu \sigma_{\Delta G^* \Delta G^*} + E \Delta \delta \sigma_{\Delta G^* \Delta G^*}$$
\[= \mu \sigma_{\Delta G^*} \Delta G^* \]

\[\sigma_{\Delta G}^2 \approx Cov(\delta \Delta G^* + G^* \Delta \delta, \delta \Delta G^* + G^* \Delta \delta)\]

\[= (\mu^2 + v)\sigma_{\Delta G^*} \Delta G^* + 2vE\sigma_{G^*}^2 + 2Cov(\delta \Delta G^*, \Delta \delta\Delta G^*)\]

\[= (\mu^2 + v)\sigma_{\Delta G^*} \Delta G^* + 2vE\sigma_{G^*}^2 + vG^* \sigma_{\Delta G^*} \Delta G^*/2\]

\[= (\mu^2 + 2v)\sigma_{\Delta G^*} \Delta G^* + 2vE\sigma_{G^*}^2/\mu^2\]

Thus

\[\sigma_{\Delta G^*} \Delta G^* \approx \frac{\sigma_{\Delta G}^2 - 2vE\sigma_{G^*}^2/\mu^2}{\mu^2 + 2v}\]

and so

\[\lambda = \mu^2 \sigma_{\Delta G^*} \Delta G^*/\sigma_{\Delta G}^2 = \mu^2 \frac{1 - \frac{2vE\sigma_{G^*}^2}{\mu^2 \sigma_{\Delta G}^2}}{\mu^2 + 2v}\]

\[\approx 1 - 2vE\sigma_{G^*}^2/\mu^2\]

In turn, \((E\sigma_{G^*}^2/\sigma_{\Delta G}^2) = (1 + (E\sigma_{G^*})^2)/(1 - \text{autocorr.} G)\). As Table A1 shows, this ranges between 1.8 and 4.8 (for cod); thus \(\lambda \approx 1\). The \(\rho^2\) terms can be ignored because, as row 4 of Table 1.4 shows, the correlation in measured daily changes in the two ports is very small. In fact, it never exceeds .11. Since by the port agents testimony, \(\mu \approx .9\), the scale effect dominates and \(a_{G^*}\) is slightly biased away from zero. Although \(a_{B}\) is also biased away from zero, that bias is also small. Thus we conclude that the true differential effect on price of quantities landed in the two ports is at least as great as we have measured it to be.
II. Dependant Coverage Ratio

Let $\xi$ represent the change in unrecorded Gloucester landings. Then

$$plima_{G,OLS} = a_B + \frac{a_G}{1 - \rho^2} \left[ \frac{\sigma_{\xi \Delta G}}{\sigma_{\Delta G}^2} - \frac{\sigma_{\xi \Delta B \sigma_{\Delta B \Delta G}}}{\sigma_{\Delta G}^2 \sigma_{\Delta B}^2} \right]$$

$$= a_G \left[ 1 + \frac{\sigma_{\xi \Delta G}}{\sigma_{\Delta G}^2} - \frac{\sigma_{\xi \Delta B \sigma_{\Delta B \Delta G}}}{\sigma_{\Delta G}^2 \sigma_{\Delta B}^2} \right]$$

where $\rho$ is the correlation coefficient between between $\Delta B$ and $\Delta G$. Likewise,

$$plima_{B,OLS} = a_B + a_G \left[ \frac{\sigma_{\xi \Delta B}}{\sigma_{\Delta B}^2} - \frac{\sigma_{\xi \Delta G \sigma_{\Delta B \Delta G}}}{\sigma_{\Delta G}^2 \sigma_{\Delta B}^2} \right]$$

It is reasonable to suppose that $\sigma_{\xi \Delta B} = (1 - \delta)\sigma_{\Delta B \Delta G}$, where $\delta$ is now considered to be constant and about .9. Define $\psi$ so that $\sigma_{\xi \Delta G}/\psi \sigma_{\Delta G}^2$, we should expect that $0 < \psi < 1 - \delta$, but that the two parameters are of the same magnitude. Then

$$plim(a_{G,OLS} - a_G) \approx a_G[\psi - (1 - \delta)\rho^2] \approx a_G \psi < 0$$

$$plim(a_{B,OLS} - a_B) \approx a_G(1 - \delta - \psi)\sigma_{\Delta B \Delta G}/\sigma_{\Delta B}^2 \approx 0$$

noting, from Table 1.4, that $\sigma_{\Delta B \Delta G}$ is typically an order of magnitude less than $\sigma_{\Delta B}^2$. 
Table 1.1: Total quantity landed (in thousands of pounds).

<table>
<thead>
<tr>
<th>Year</th>
<th>Boston</th>
<th>Gloucester</th>
<th>Boston</th>
<th>Gloucester</th>
</tr>
</thead>
<tbody>
<tr>
<td>1908</td>
<td>76,030</td>
<td>106,007</td>
<td>65,139</td>
<td>60,582</td>
</tr>
<tr>
<td>1939</td>
<td>295,353</td>
<td>75,766</td>
<td>276,843</td>
<td>67,443</td>
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<tr>
<td>1944</td>
<td>151,762</td>
<td>188,661</td>
<td>129,951</td>
<td>145,129</td>
</tr>
<tr>
<td>1959</td>
<td>113,257</td>
<td>228,722</td>
<td>109,272</td>
<td>81,930</td>
</tr>
<tr>
<td>1964</td>
<td>124,020</td>
<td>140,445</td>
<td>105,000</td>
<td>63,924</td>
</tr>
<tr>
<td>1969</td>
<td>57,675</td>
<td>80,250</td>
<td>43,452</td>
<td>34,156</td>
</tr>
<tr>
<td>1974</td>
<td>31,485</td>
<td>133,845</td>
<td>23,363</td>
<td>31,466</td>
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<tr>
<td>1979</td>
<td>34,320</td>
<td>166,545</td>
<td>26,792</td>
<td>31,466</td>
</tr>
<tr>
<td>1984</td>
<td>17,925</td>
<td>168,915</td>
<td>16,643</td>
<td>64,184</td>
</tr>
<tr>
<td>1989</td>
<td>15,105</td>
<td>94,275</td>
<td>14,218</td>
<td>20,763</td>
</tr>
<tr>
<td>1992</td>
<td>12,480</td>
<td>96,885</td>
<td>12,033</td>
<td>19,294</td>
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Table 1.2: Mean yearly quantity landed, 1982-1992.

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<th>Boston’s share</th>
</tr>
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<tr>
<td>Cod</td>
<td>6,678</td>
<td>16,300</td>
</tr>
<tr>
<td>Cusk</td>
<td>443</td>
<td>1,061</td>
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<tr>
<td>Y. Flounder</td>
<td>227</td>
<td>964</td>
</tr>
<tr>
<td>Ame. Flounder</td>
<td>1,010</td>
<td>3,983</td>
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<tr>
<td>Haddock</td>
<td>1,912</td>
<td>5,089</td>
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<tr>
<td>Hake</td>
<td>1,112</td>
<td>3,454</td>
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<tr>
<td>Redfish</td>
<td>1,294</td>
<td>1,853</td>
</tr>
<tr>
<td>Pollock</td>
<td>4,358</td>
<td>10,500</td>
</tr>
<tr>
<td>Wolfish</td>
<td>221</td>
<td>472</td>
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</table>

31
<table>
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<tr>
<th>Species</th>
<th>dollar/pound</th>
<th>mean</th>
<th>s.d.</th>
<th>mean</th>
<th>s.d.</th>
<th>mean</th>
<th>s.d.</th>
<th>mean</th>
<th>s.d.</th>
<th>mean</th>
<th>s.d.</th>
<th>mean</th>
<th>s.d.</th>
<th>mean</th>
<th>s.d.</th>
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<tr>
<td>Drawn Pollock</td>
<td></td>
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<tr>
<td>Whole Hake</td>
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<td></td>
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</tr>
<tr>
<td>Large American Flounder</td>
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<tr>
<td>Mean dollar/pound</td>
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</tbody>
</table>

Table I.3: Summary Statistics.
Table 1.4: Ordinary least squares. Landings are in million pounds. Prices are dollars per pound.

<table>
<thead>
<tr>
<th></th>
<th>L. Cod</th>
<th>Cusk</th>
<th>Yellow-tail Fl.</th>
<th>Large Am. Fl.</th>
<th>L. Haddock</th>
<th>Wh. Hake</th>
<th>Unclass. Redfish</th>
<th>Drawn Pollock</th>
<th>Wolf-fish</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gloucester price</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Boston</td>
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<td>-12.4</td>
<td>-1.4</td>
<td>-18.7</td>
<td>-9.5</td>
<td>-1.6</td>
<td>-.4</td>
<td>-1.0</td>
<td>-22.7</td>
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<tr>
<td></td>
<td>(.17)</td>
<td>(1.9)</td>
<td>(4.5)</td>
<td>(1.9)</td>
<td>(.79)</td>
<td>(1.8)</td>
<td>(.3)</td>
<td>(.2)</td>
<td>(3.1)</td>
</tr>
<tr>
<td>Gloucester</td>
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<td>-9.0</td>
<td>-13.6</td>
<td>-12.9</td>
<td>-4.9</td>
<td>-9.3</td>
<td>-2.4</td>
<td>-1.4</td>
<td>-26.4</td>
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<tr>
<td></td>
<td>(.09)</td>
<td>(1.0)</td>
<td>(2.4)</td>
<td>(0.6)</td>
<td>(.32)</td>
<td>(.9)</td>
<td>(.3)</td>
<td>(1)</td>
<td>(2.0)</td>
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<tr>
<td>D.W.</td>
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<td>.54</td>
<td>.53</td>
<td>.65</td>
<td>.73</td>
<td>.74</td>
<td>.79</td>
<td>.56</td>
<td>.62</td>
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<td></td>
<td></td>
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<tr>
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<td>-24.5</td>
<td>-12.5</td>
<td>-1.6</td>
<td>-3.2</td>
<td>-1.7</td>
<td>-29.4</td>
</tr>
<tr>
<td></td>
<td>(.20)</td>
<td>(2.7)</td>
<td>(5.5)</td>
<td>(2.2)</td>
<td>(1.0)</td>
<td>(2.1)</td>
<td>(.6)</td>
<td>(.2)</td>
<td>(3.6)</td>
</tr>
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<td>Gloucester</td>
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<td>-11.0</td>
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<td>-11.5</td>
<td>-5.4</td>
<td>-1.6</td>
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<tr>
<td></td>
<td>(.11)</td>
<td>(1.3)</td>
<td>(3.0)</td>
<td>(7.1)</td>
<td>(4.5)</td>
<td>(1.0)</td>
<td>(.5)</td>
<td>(1)</td>
<td>(2.4)</td>
</tr>
<tr>
<td>D.W.</td>
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<td>.62</td>
<td>.68</td>
<td>.73</td>
<td>.54</td>
<td>.69</td>
<td>.48</td>
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<tr>
<td>Number of Obs.</td>
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<td>1338</td>
<td>632</td>
<td>1438</td>
<td>1409</td>
<td>649</td>
<td>1108</td>
<td>1210</td>
<td>1304</td>
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</table>
### Table I.2: Non-linear least squares: quasi-differencing

<table>
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<tr>
<th>Year</th>
<th>L. Cod</th>
<th>Cape Cod</th>
<th>Yellow Tail Fl.</th>
<th>Large Am. Fl.</th>
<th>L. Haddock</th>
<th>Wh. Hake</th>
<th>Unclass.</th>
<th>Redfish</th>
<th>Drawn Pollock</th>
<th>Wolf-fish</th>
</tr>
</thead>
<tbody>
<tr>
<td>1989</td>
<td>0.31</td>
<td>-5.35</td>
<td>-1.8</td>
<td>-2.97</td>
<td>-2.42</td>
<td>-1.80</td>
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<td>-0.37</td>
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<tr>
<td></td>
<td>(0.06)</td>
<td>(0.84)</td>
<td>(1.7)</td>
<td>(0.65)</td>
<td>(0.34)</td>
<td>(1.04)</td>
<td>(0.22)</td>
<td>(0.10)</td>
<td>(1.46)</td>
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<td>1990</td>
<td>0.10</td>
<td>-0.81</td>
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<td>(0.42)</td>
<td>(1.1)</td>
<td>(0.26)</td>
<td>(0.17)</td>
<td>(0.54)</td>
<td>(0.20)</td>
<td>(0.07)</td>
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Boston price

<table>
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<tr>
<th>Year</th>
<th>L. Cod</th>
<th>Cape Cod</th>
<th>Yellow Tail Fl.</th>
<th>Large Am. Fl.</th>
<th>L. Haddock</th>
<th>Wh. Hake</th>
<th>Unclass.</th>
<th>Redfish</th>
<th>Drawn Pollock</th>
<th>Wolf-fish</th>
</tr>
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<tbody>
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<td>1989</td>
<td>0.62</td>
<td>-12.4</td>
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<td>-6.19</td>
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<tr>
<td></td>
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<td>(1.97)</td>
<td>(2.28)</td>
<td>(0.84)</td>
<td>(0.46)</td>
<td>(0.76)</td>
<td>(0.33)</td>
<td>(0.10)</td>
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<td>-0.95</td>
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<tr>
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Boston price

<table>
<thead>
<tr>
<th>Year</th>
<th>L. Cod</th>
<th>Cape Cod</th>
<th>Yellow Tail Fl.</th>
<th>Large Am. Fl.</th>
<th>L. Haddock</th>
<th>Wh. Hake</th>
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<th>Redfish</th>
<th>Drawn Pollock</th>
<th>Wolf-fish</th>
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<tr>
<td>1989</td>
<td>0.89</td>
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<td>0.87</td>
<td>0.93</td>
<td>0.86</td>
<td>0.91</td>
<td>0.80</td>
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<tr>
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<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.01)</td>
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<td>(0.02)</td>
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<td>(0.01)</td>
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No. of Obs. 1606 1338 632 1438 1409 649 1108 1210 1304
Table 1.6: Non-linear least squares: logarithmic inverse demand curve. \( Q_B \) and \( Q_G \) are, respectively, quantities landed at Boston and Gloucester, in millions of pounds. Price is in dollars per pound.

<table>
<thead>
<tr>
<th></th>
<th>L. Cod</th>
<th>Cusk</th>
<th>Yellow-tail Fl.</th>
<th>Large Am. Fl.</th>
<th>L. Haddock</th>
<th>Wh. Hake</th>
<th>Unclass. Redfish</th>
<th>Drawn Pollock</th>
<th>Wolf-fish</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gloucester price</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \ln(Q_B + \beta Q_G) )</td>
<td>-.017</td>
<td>-.016</td>
<td>.005</td>
<td>-.020</td>
<td>-.040</td>
<td>-.015</td>
<td>-.007</td>
<td>-.014</td>
<td>-.006</td>
</tr>
<tr>
<td>( \beta )</td>
<td>.57</td>
<td>.14</td>
<td>2.55</td>
<td>.22</td>
<td>.14</td>
<td>.51</td>
<td>.22</td>
<td>.50</td>
<td>.14</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>.93</td>
<td>.88</td>
<td>.88</td>
<td>.94</td>
<td>.90</td>
<td>.82</td>
<td>.71</td>
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<td></td>
</tr>
<tr>
<td>( \ln(Q_B + \beta Q_G) )</td>
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<td>.004</td>
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<td>-.038</td>
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<td>.87</td>
<td>.92</td>
<td>.85</td>
<td>.91</td>
<td>.80</td>
<td>.86</td>
<td>.88</td>
</tr>
</tbody>
</table>

|                  |        |      |                 |               |            |          |                  |               |           |
|                  |     (.002) | (.002) | (.005) | (.004) | (.004) | (.007) | (.002) | (.003) | (.003) |
|                  | (.19) | (.07) | (9.80) | (.14) | (.05) | (.71) | (.28) | (.27) | (.24) |
|                  | (.01) | (.01) | (.02) | (.01) | (.01) | (.02) | (.02) | (.02) | (.01) |

|                  |        |      |                 |               |            |          |                  |               |           |
|                  |     (003) | (.005) | (.006) | (.005) | (.006) | (.005) | (.003) | (.002) | (.002) |
|                  | (.06) | (.10) | (361.2) | (.14) | (.05) | (.05) | (.10) | (.07) | (.13) |
|                  | (.01) | (.02) | (.02) | (.01) | (.01) | (.02) | (.02) | (.01) | (.01) |
Table 1.7: The price of cod: non-linear least squares (quasi-differencing).

$B_t$, $G_t$ and $Port_t$ are daily quantities landed in Boston, Gloucester and Portland, respectively, in millions of pounds. $Price$ is mean price in the port, denominated in dollars per pound. $Price_{t-1}$ is the previous day's price. The sample for columns (1) and (2) include days for which there were landings in both Boston and Gloucester on that and the previous day. Columns (3)-(5) require landings in those two ports and Portland on that day the previous two days.

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
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<th></th>
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</thead>
<tbody>
<tr>
<td>$\Delta_\alpha B_t$</td>
<td>-.31</td>
<td>-.62</td>
<td>-.39</td>
<td>-.75</td>
<td>-.16</td>
<td>-.24</td>
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<td>(.06)</td>
<td>(.09)</td>
<td>(.08)</td>
<td>(.13)</td>
<td>(.10)</td>
<td>(.15)</td>
</tr>
<tr>
<td>$\Delta_\alpha G_t$</td>
<td>-.10</td>
<td>-.18</td>
<td>-.14</td>
<td>-.28</td>
<td>-.05</td>
<td>0.59</td>
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<tr>
<td></td>
<td>(.03)</td>
<td>(.05)</td>
<td>(.05)</td>
<td>(.08)</td>
<td>(.06)</td>
<td>(.10)</td>
</tr>
<tr>
<td>$\Delta_\alpha B_{t-1}$</td>
<td>-.13</td>
<td>-.31</td>
<td>-.13</td>
<td>-.31</td>
<td>-.05</td>
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<td>(.07)</td>
<td>(.11)</td>
<td>(.07)</td>
<td>(.11)</td>
<td>(.06)</td>
<td>(.10)</td>
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<tr>
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<td>-.18</td>
<td>-.08</td>
<td>-.18</td>
<td>-.05</td>
<td>0.59</td>
</tr>
<tr>
<td></td>
<td>(.04)</td>
<td>(.07)</td>
<td>(.04)</td>
<td>(.07)</td>
<td>(.06)</td>
<td>(.10)</td>
</tr>
<tr>
<td>$\Delta_\alpha Port_t$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.14</td>
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</tr>
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<td></td>
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<td></td>
<td></td>
<td>(.12)</td>
<td>(.16)</td>
</tr>
<tr>
<td>$Price_{t-1}$</td>
<td>.93</td>
<td>.89</td>
<td>.96</td>
<td>.90</td>
<td>.90</td>
<td>.86</td>
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<td>(.01)</td>
<td>(.02)</td>
<td>(.01)</td>
<td>(.02)</td>
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<tr>
<td>Number of Obs.</td>
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<td>1606</td>
<td>1034</td>
<td>1034</td>
<td>1034</td>
<td>300</td>
</tr>
</tbody>
</table>
Table 1.8: Covariances and correlations. Units are millions of pounds

<table>
<thead>
<tr>
<th></th>
<th>Large Cod</th>
<th>Cusk</th>
<th>Yellow-tail Fl.</th>
<th>Large Am. Fl.</th>
<th>L. Haddock</th>
<th>Wh. Hake</th>
<th>Unclass. Redfish</th>
<th>Dr. Pollock</th>
<th>Wolffish</th>
</tr>
</thead>
<tbody>
<tr>
<td>Var((\Delta B))</td>
<td>1000</td>
<td>7.3</td>
<td>8.7</td>
<td>23</td>
<td>180</td>
<td>41</td>
<td>140</td>
<td>720</td>
<td>2.9</td>
</tr>
<tr>
<td>Var((\Delta G))</td>
<td>2800</td>
<td>.30</td>
<td>.23</td>
<td>150</td>
<td>710</td>
<td>150</td>
<td>180</td>
<td>1700</td>
<td>5.2</td>
</tr>
<tr>
<td>Cov((\Delta B, \Delta G))</td>
<td>60</td>
<td>.21</td>
<td>.45</td>
<td>5.2</td>
<td>39</td>
<td>-.96</td>
<td>21</td>
<td>120</td>
<td>.018</td>
</tr>
<tr>
<td>Corr((\Delta B, \Delta G))</td>
<td>.036</td>
<td>.015</td>
<td>.032</td>
<td>.088</td>
<td>.110</td>
<td>-.012</td>
<td>.135</td>
<td>.107</td>
<td>.005</td>
</tr>
</tbody>
</table>
2

The price effect of widening fish markets through electronic auctions

Patrice Guillotreau (Université de Nantes & Institut de Recherche pour le Développement) and Pablo Jiménez-Toribio (Universidad de Huelva)

Fish markets can be extended by two means, first by attracting newcomers in a local trading room and secondly by allowing remote bidders to participate. In both cases, electronic systems have played a key role in the French primary fish markets. The computerisation of trading rooms started in the mid-1980s while the connection through Intranet or Internet systems only started a few months ago. However, if any system is now feasible through the use of new technologies of information, the socio-economic outcome of extended markets is far from being clearly foreseeable. By using a structural break searching procedure, this paper presents evidence of price increases after the implementation of local electronic auction systems. A brief survey of interconnection experiences of fish markets in France is used to consider the economic consequences of remote bidding on fish prices.

2.1 Introduction

This paper\(^1\) looks empirically at the impact of widening fish markets by electronic means on price levels. Two different ways of widening

\(^1\)This communication is largely inspired by previous works realised in co-authorship and particularly by two publications (Guillotreau P. and R. Jiménez Toribio 2006; LEN-Corrail 2007). Special thanks are addressed to L. Baranger, F. Gonzales, L. Le Grel and A. Rubin (Univ. of Nantes, France) and to Sandro Sapio (Univ. of Naples Parthenope and Sant’Anna School of Advanced Studies, Italy) for his useful comments on the first draft of this chapter.

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markets are made possible by the use of new technology: either by attracting new buyers in local or network trading rooms, or more recently in France by authorising remote bidders to buy in a local fish market. What can be expected in terms of prices and market organisation from such changes?

The theoretical conditions of different auction systems resulting in different outcomes are well known in economics since Vickrey’s seminal findings (Vickrey 1961, Wolfstetter 1996, Klemperer 1999, Maskin and Riley 2000). Previous empirical studies also showed a price difference when comparing a mere direct sales system to an auction system in the specific case of fish markets (Armstrong 2001, Helstad et al. 2005). When it comes to the impact that electronic auction systems may have on the price levels and market organisation, empirical analyses are very rare and the expected outcome is unclear (Graham 1999). The computerisation of trading rooms usually precedes the wider interconnection of market places by remote bidding through Internet. Overall, the present high degree of competition for most species of fish would expect a low impact from interconnection on local prices. Indeed, an auctioneer stated in 1993: “theoretically (sic), interconnection increases the potential number of buyers, harmonises the prices and reduces the gaps between ports, but this reality does not resist to the reality of facts” (Le Marin, December 1993). It is nonetheless hard to believe that distant intruders in the auction system, by disrupting the social game in force in most fish markets, will not create asymmetry, new risk perception and therefore new behaviours by local traders. The present study hypothesises that the implementation of electronic devices is not neutral on prices, even though the market organisation itself remains unchanged (ascending auction regime for instance).

In the present study (first section), evidence is given through a multiple break searching procedure (Bai and Perron 1998, 2003a, 2003b) that the mere adoption of electronic auction systems - substituted for previous shout auction or pairwise trading in two French ports - has increased both price levels and volatility of live prawns (Nephrops norvegicus) (Guillotreau and Jiménez-Toribio 2006). Secondly, more changes are expected from the recent introduction of remote bidding access. Although too recent to be econometrically tested by the same means, some substantial effects have already been perceived by the users and a few preliminary results, based on a survey of the French auctioneers, are shown in the second part of the paper.
2.2 Impact of a local electronic trading system on shellfish prices

2.2.1 The introduction of electronic bidding systems in primary fish markets in France

Auction markets are the prevalent trading institution in wild-caught seafood markets (Anderson and Martinez-Garmendia 2003). In France, their introduction in big harbours such as Boulogne sur Mer or Concarneau dates back to the late 19th century but could be even older (Matras-Guin 1987). The initial adoption of auction systems was nonetheless controversial: “In the mid-19th century, there was resistance to auctioning in British livestock markets because sellers feared collusion between buyers” (Graham 1999: 176). Nowadays, fishermen still complain about the supposed market power of primary buyers in the auction room and refuse to give information about their catches ahead of sales (Debril 2000).

Electronic trading systems

Electronic clock auction systems (ECAS) have been introduced as a solution to the imbalance between buyers and sellers in favour of the latter: the objective of a major supplier of electronic trading systems in Europe is “to make (your) market more competitive, more transparent, and try to keep the added value on the production level as much as possible” (Graham 1999: 178). Other motivating factors can influence the decision of implementing such electronic markets, like authorising thereafter remote buyers to join the sale system. Fish markets can therefore be broadened either by introducing local newcomers having different private values (mongers vs processors), or by attracting remote bidders through Internet. The socioeconomic implications are different because remote bidding access imposes important efforts in terms of “framing” (Callon 1998, Debril and de Saint Laurent 2003) and new habits for bidders like non-viewing procurement. The majority of primary fish markets are now electronically equipped but very recently one third of the French fish markets allowed distant bidders to buy fish. In that respect, what are the outcomes of this new market organisation, particularly in terms of price changes? This paper gives an empirical picture of these new trading organisations.

The trading organisation “varies from location to location, for little
obvious reason” (Kirman 2001: 157). It is likewise for the introduction of electronic bidding systems. Countries like France or Spain are considered as very open to the implementation of electronic systems, whereas this is not at all the case in the United Kingdom\(^2\) or Japan (Luc Schelfhout, cited by Graham 1999, p.183; Bestor 2004).

In France, the first experience was attempted in Lorient as early as 1979 but it was given up rapidly after a month because the operators mistrusted the use of technology. New electronic bidding systems took place in the mid-1980s (Port-en-Bessin 1986, Sète 1986, Saint-Guénolé 1987, Le Croisic 1988, La Rochelle 1988). In most cases, the use of electronic technology was limited to a local computerised trading room. In 1993, only one third of the fish auction markets in France had substituted the shout system for an electronic device. A decade later the proportion of equipped harbours is over 75% of the 40 fish auction markets (Fig. 2.1b). Very few marketplaces have retained the old shout auction system despite its flexibility. For instance, some traditional auctioneers can choose alternatively a descending or ascending system if they estimate that the price is respectively too high or too low.

The auditorium trading system fits more with the Walrasian view of “perfect markets” but mobile systems were implemented in many important harbours as a “surrogate for negotiating the social structure of the market network” (Graham 1999, p. 14). The so-called “Moby-clock” system was implemented by Aucxis Trading Systems (ATS) as “an electronic auction clock mounted on a battery powered vehicle which can move through the auction hall” (ibid, p.182). Fish are not conveyed on a rolling bed, but the electronic clock itself is driven by the auctioneer around the fish boxes. Consequently, bidders can see the fish. They are displayed face-to-face around the boxes and can also observe each others’ behaviour, even though the button can be pressed very discretely. In most cases producers are also willing to use this “close-to-the-fish” system because quality can be more easily compared between products.

\(^2\)The experiences of Lochinver and Kinlochbervie are very interestingly developed by Graham (1999, p. 184-198). Two arguments were used by opponents to electronic markets: the sales of important lots reduce the time advantage of implementing Dutch electronic auctions, the cost of grading fish for remote bidding could have been important. Mostly, local buyers feared to “lose” the fish that may have been sold in other continental ports. A conflict of interests between the harbour owner (Highland Harbours) and the managing company (Lochinver fishselling company) also appeared to have played a significant role in this failure.
The choice of the auction system

The type of sale differs substantially from one fish market to another (Armstrong 2001): ascending English auctions, descending Dutch auctions, Japanese auctions through a closed-seal bid, second-price (or Vickrey) auctions, etc. In Europe, two systems are commonly implemented: English and Dutch auction systems.

Amazingly, in France the most widespread system is a mixture of descending and ascending bidding (Fig. 2.1 a). This is not the first choice of the auctioneers because this system takes a longer time to sell fish than a Dutch system which has the reputation of bringing more transparency into the system (Debril and de Saint Laurent 2003). But it quite closely reproduces the former shout auction system and gives bidders more opportunity to exchange information during the sale. An opening price is proposed by the auctioneer before going down around the clock. When a buyer makes a bid the clock stops with three lights being switched on for about one second each. During this signalled delay, other bidders may intervene with a higher bid, until a single buyer remains in the auction. This system looks more like an English auction system and takes more time than a simple Dutch system (which ends with the first bid). This explains why the latter is preferred in markets for coastal species where the number of lots is higher (wider variety of species, smaller quantities).
2.2.2 Expected impact on prices

Weak empirical evidence

The empirical impact of different auction systems remains unclear. The argument that would convince most fishermen of the benefits of (electronic) auctions would be the fact that their introduction leads to the payment of higher prices for their fish. Whilst there is anecdotal evidence that this can be the case, the underlying arguments for the achievement of higher prices at electronic auctions are weak (Carleton 2000: 56-57). Higher prices are nonetheless observed in fish auction markets as compared to direct sales according to Helstad et al. (2005: 307). Supply-side explanations are proposed (higher costs of handling fish, homogeneous lots, smaller quantity sold through auctions, etc.) but, surprisingly, no reference is made to the market organisation itself and the way buyers meet sellers.

Whatever the impact on prices, the period of time of sales, particularly in the case of Dutch bidding, it is considerably shorter, resulting in significant improvements (higher quality of fish, no congestion of suppliers, faster access to consumer markets). Some estimates suggest that organising sales between 25 suppliers and 25 buyers would take around 3 hours in a live (shout) system, against only half an hour with a Dutch electronic system (Graham 1999: 183). However, other evidence in Lorient shows that sales in pairwise trading simultaneously takes shorter time than electronic bidding organised lot by lot.

Theoretical expectations

Four decades ago, Vickrey demonstrated the equivalence of revenue between Dutch and English auctions (Vickrey 1961). The equivalence means that the expected revenue is the same and that rational bidders follow the same strategy whatever auction system is in force. The theorem of revenue equivalence is based on four central assumptions:

- Bidders cannot be split into groups with members of one group systematically valuing the item higher than members of other groups (symmetry of bidders);
- Their private bid values are independent and identically distributed (iid) (non affiliation);
- Bidders and sellers are risk-neutral;
• Payments are a function of bids only (and not of travel distance for example).

When relaxing these assumptions, the revenue equivalence theorem (RET) does not necessarily hold and prices can differ according to the system in use (Armstrong 2001; Klemperer 1999; Milgrom and Weber 1982; Wolfstetter 1996). For instance, in asymmetric auctions where private values are not drawn from an identical probability distribution, a Dutch auction system may not select the bidder who has the highest private value. Bidders with higher valuations tend to submit a bid below their private value because their probability of winning the bid is higher due to the presence of other bidders having a lower private valuation. They can therefore bid less aggressively to outbid the competitors, depending on the distribution of the two groups.

Secondly, independence means that private values are not positively correlated. When they are, it affects the outcome of a Dutch auction system negatively, unlike an English auction system where the affiliated bidders tend to bid more aggressively. In the latter case, they do so because the bidders who remain in the auction can observe that other bidders have also remained in the bidding process. Therefore they can infer that these other bidders’ valuations of the commodity are at least as high as the current price.

Finally, Dutch systems are also affected by the perception of risk. The bidders with higher valuations are less likely to hide their preferences if they are unwilling to lose the auction by waiting too long. Dutch systems can therefore lead to higher prices than those achieved with English systems as a result of buyers responses to the risk of losing the lot.

2.2.3 A structural break model applied to a shellfish price relationship

In order to test for the impact of implementing electronic auction systems on fish prices, a time series analysis is undertaken by comparing the dynamics of prices for the same product (live prawns, *Nephrops norvegicus*) in two French ports (Lorient and Le Guilvinec) which are 150 km apart and introduced an electronic auction system at nearly the same date. The data are first introduced, then the econometric models and finally the results are described.
Data

Two different fish markets are selected to illustrate the variety of auction systems: Lorient and Le Guilvinec. Both have experienced a concurrent implementation of electronic trading system respectively in March and April 2002. Lorient offers a dual system for coastal and offshore fleets. The latter have been selling fish in a trading room with descending-ascending auctions since March 1999. On March 19th 2002, the market for coastal species was totally re-organised with the implementation of a Dutch bidding system in the fish hall. Prior to that system the fishermen used to sell shellfish in a pairwise trading organisation. This system has been described in the case of the Marseille wholesale fish market (Haerdle and Kirman 1995; Weisbuch et al. 2000; Kirman 2001) which looks very similar to the system previously in force in Lorient. All transactions were bilateral and no prices were posted. “There is little negotiation, and prices can reasonably be regarded as take-it-or-leave-it prices given by the seller” (Kirman 2001: 159).

The second example is given by seven ports of south Brittany, all managed by a single entity, the Chamber of Commerce and Industry of Quimper. One of these ports - Saint Guénolé - implemented a Dutch system in a trading auditorium in July 1987. Six neighbouring shout auction systems - including that of Le Guilvinec - were equipped in one week five years later (April 2002) by mobile ECAS, with a descending-ascending bidding process, similar to the offshore fish market in Lorient. It is difficult to isolate the pure effect of electronic markets on prices from other effects. Prices for the same species can fluctuate greatly between different ports because of quality, different grading systems, low volumes, etc. The two Breton ports - Lorient and Le Guilvinec - were chosen to compare the price levels ($P_l$ and $P_g$) of the same commodity - live prawns ($Nephrops norvegicus$) - with two different auction systems implemented at around the same date. These two fish auction markets are separated by a distance of about 150 km and one of them - Le Guilvinec - is the market of reference for these products. The two markets are more or less equal in terms of landings, with an average of 770 and 600 tons respectively of live prawns per year. The sample of average nominal weekly prices covers the period between January-1 1999 and December-52 2003 (Fig. 2.2), and shows a differential in law of one price, i.e., by the extent to which supply and demand shocks are transmitted from one market to another. The elasticity of price

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3 More comprehensive results can be found in Guillotreau and Jiménez-Toribio (2006).
transmission should then be estimated as close as possible to unity. Such a hypothesis relies on low transaction and transportation costs for homogeneous goods, which is the case for live prawns of the same quality type sold in two fairly close markets where some of the primary processors are present in the two ports. Note that the two regions do not have to trade for their markets to be integrated: it is sufficient that buyers and sellers regard the two locations as alternatives (*ibid*).

Market integration is usually investigated by using prices in logarithmic form. This functional form is convenient to linearise a market integration or a mark-up model (of the type \( p_1 = \alpha p_2^\beta \)) as it then offers the opportunity of testing the value of \( \beta \) (i.e. the elasticity of transmission between the two prices) which should be close to unity in the case of perfect market integration. Before estimating univariate and VAR models, several types of unit root tests, with different assumptions about the presence of a structural break, were performed on the two series (Augmented Dickey Fuller, Phillips-Perron, Dickey-Fuller-GLS, KPSS, ZA).\(^4\) Substantial evidence of stationarity is found for the two series. In most papers, time series of prices are found to be I(1). In our case study the series were, surprisingly, found to be I(0) which led us to use standard econometric techniques instead of cointegration.

### A multiple break searching procedure

Bai and Perron (1998, 2003a, 2003b) consider several structural changes in an economic relationship estimated by least squares. The time series properties need to be first identified because this technique is only applicable to stationary data. The main contribution of Bai and Perron lies in the partial structural change modelling that the procedure offers. They propose several tests to determine the number of structural breaks in a relationship. One of these tests considers the null hypothesis of \( l \) change(s) against the alternative hypothesis of \( l + 1 \) changes.

The Bai and Perron (1998, 2003a, 2003b) model can be expressed as follows:

\[
y_t = x_t' \beta + z_t' \delta_1 + u_t \quad t = 1, \ldots, T_1
\]

\[
y_t = x_t' \beta + z_t' \delta_2 + u_t \quad t = T_1, \ldots, T_2
\]

\[
\vdots
\]

\(^4\)The results can be found in Guillotreau and Jiménez-Toribio (2006).
Figure 2.2: Weekly Prices (Eur/kg) of live prawns in Lorient and Le Guilvinec. Source: Réseau Inter Criées (RIC) - Ofimer.
\[ y_t = x_t' \beta + z_t' \delta_{m+1} + u_t \quad t = T_m, \ldots, T \]

where \( y_t \) represents the dependent variable, \( x_t \) and \( z_t \) are vectors of covariates with \((p \times 1)\) and \((q \times 1)\) elements respectively, \( \beta \) and \( \delta_j \) \((j = 1, \ldots, m + 1)\) are the corresponding vectors of coefficients. The indices \((T_1, T_2, \ldots, T_m)\) denote the unknown breakpoints. In a pure structural change model, all coefficients are subject to changes at the same date and the corresponding variables should then be placed in \( z_t \) \((p = 0)\). In a partial structural change model, some of the variables whose coefficients are not subject to changes are placed in \( x_t \) \((p \leq 0)\).

**Univariate models**

As mentioned above, an advantage of the ECAS in that it reduces collusion among buyers. Therefore, this improvement of technology may increase the price in the market, irrespective of what happens in the other market. For this reason, univariate models have been considered in order to determine the impact of the ECAS on the price of each market.

Using the multiple break searching procedure described in previous section, the price of live prawns in Lorient and Le Guilvinec are first analysed through the following model:

\[ y_t = \mu_j + \sum_{i=1}^{51} \alpha_i SD_i + \rho y_{t-1} + u_t \quad t = T_{j-1} + 1, \ldots, T_j \quad (2.2) \]

for \( j = 1, \ldots, m + 1 \), where \( m \) is the potential number of breaks. The convention \( T_0 = 0 \) and \( T_{m+1} = T \) is used. \( y_t \) represents the variables \( Pl \) (Logarithm of the price in Lorient) and \( Pg \) (Logarithm of the price in Le Guilvinec), \( \mu_j \) is the intercept (subject to structural change), \( SD_i \) represent 51 seasonal dummies (not subject to structural change), \( y_{t-1} \) is the one period lagged price (\( \rho \) not being subject to structural change) and \( u_t \) is the error term. Hence, the breaks are assumed to be in the constant of the regression.

The autoregressive term has been introduced to eliminate the serial correlation of the residuals. The Ljung-Box (LB) test for serial correlation has been performed for both models. Results of the Bai-Perron procedure for \( Pl \) and \( Pg \) are given in Tables 2.3 and 2.4 (annex), respectively. No problems of serial correlation were encountered in the residuals of the two models at the 5\% significance level. For Lorient, one single break date was selected by most of the criteria on week 2002:14 (April
1st 2002), i.e. just following the introduction of the electronic system. Once we have estimated model in Eq. 2.2 for the Lorient prices, the model can be expressed as follows:

\[
Pl_t = (0.16) 2.34 + \sum_{i=1}^{51} \alpha_i SD_i + (0.06) 0.19 Pl_{t-1} + u_t \quad t = 1999 : 2, ..., 2002 : 14
\]  

(2.3)

\[
Pl_t = (0.17) 2.49 + \sum_{i=1}^{51} \alpha_i SD_i + (0.06) 0.19 Pl_{t-1} + u_t \quad t = 2002 : 15, ..., 2003 : 52
\]

\[R^2 = 0.76 \quad \overline{R^2} = 0.69\]

Standard errors are in parentheses. After the break, the intercept increases, implying a relative increase of live prawn prices in Lorient since the electronic auction system came into force. For Le Guilvinec, one single break is found at week 2002:16 (April 15th 2002), i.e. the week just preceding the implementation of the ECAS. The intercept also increases, although to a lesser extent:

\[
Pg_t = (0.17) 2.07 + \sum_{i=1}^{51} \alpha_i SD_i + (0.06) 0.42 Pg_{t-1} + u_t \quad t = 1999 : 2, ..., 2002 : 16
\]  

(2.4)

\[
Pg_t = (0.18) 2.15 + \sum_{i=1}^{51} \alpha_i SD_i + (0.06) 0.42 Pg_{t-1} + u_t \quad t = 2002 : 17, ..., 2003 : 52
\]

\[R^2 = 0.82 \quad \overline{R^2} = 0.77\]

**Multivariate Vector Autoregressive (VAR) model**

The relationship between the two prices is now tested to see whether the introduction of electronic auction systems has affected the price linkage itself. If both prices have increased concurrently, the price relationship may not be modified accordingly. The analysis is achieved through the estimation of a Vector Autoregressive (VAR) model (results in Tables 2.5 and 2.6 in annex). There is
one structural break according to the sequential procedure for the first equation of the VAR model (where the price in Lorient is the dependent variable). The location of the structural break detected is 2001:52 (25 December 2001; 95% confidence interval between 2001:44 and 2002:15).

There is a structural break in the second equation of the VAR model (where the price in Le Guilvinec is the dependent variable) according to the sequential procedure. The location of the break is 2002:16 (15 April 2002; 95% confidence interval between 2001:36 and 2002:36). The former can be explained by the implementation of the euro and the latter by the implementation of the ECAS in both markets, which was at almost the same time. Impulse response models indicate that Le Guilvinec can be considered as the leading market.5

A significantly positive impact of ECAS on both market prices

The first results based on the univariate models indicates quite clearly that a single structural change matching the specific date of implementation of the electronic systems has modified the price setting conditions in the two ports considered separately. The two prices have been impacted positively after the change, with a bigger price increase in Lorient (+16%) than in Le Guilvinec (+8%), despite a larger increase in quantity in Lorient (Table 2.1).

Table 2.1: Descriptive statistics of the two periods

<table>
<thead>
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<th>Mean after April 2002</th>
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<tbody>
<tr>
<td></td>
<td>Pg</td>
<td>Pl</td>
</tr>
<tr>
<td>Mean</td>
<td>9.7</td>
<td>10.4</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>2.7</td>
<td>3.4</td>
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<tr>
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<td>0.33</td>
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<tr>
<td>Pg - Pl</td>
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<td>0.9</td>
</tr>
<tr>
<td>Coeff. of var.</td>
<td>+1%</td>
<td>+4%</td>
</tr>
</tbody>
</table>

The Moby-Clock (descending-ascending regime) introduced in Le Guilvinec does not represent such an important change for the bidders as the one in Lorient where a modern ECAS (with a descending bidding system) was substituted for the traditional pairwise trading organisation. In the latter, the market has been significantly transformed by

5The results and discussion are not detailed in this chapter but can be found in Guilloitreau and Jiménez-Toribio (2006).
newcomers and new trading behaviour. Many other fishing boats have joined Lorient because of attractive prices, and many fishmongers now come daily from towns located 100 miles away from the port because they can have an easier access to the bidding process (unlike in the previous trading organisation where local primary processors held a dominant position). The sales of live prawns in Lorient have increased from an average of 12 tons per week before the break to nearly 18 tonnes afterwards (+50%), whereas the growth was only 18% in Le Guilvinec (from 11 to 13 tons).

With regard to auction theory, several reasons may explain the bigger impact on prices in Lorient. This port has implemented a Dutch (descending) bidding system while Le Guilvinec has preferred a descending-ascending auction system, closer to an English (ascending) auction system. The revenue equivalence theorem, which asserts that equilibrium prices are independent of the auction system, only holds under certain critical assumptions (Armstrong 2001). The actual price behaviour in these two ports suggests that at least two of these assumptions do not hold in this case.

In particular, the symmetry assumption no longer holds in Lorient because some bidders (fishmongers) present higher private valuations than others (local primary processors). During the first hour of the sales, distant fishmongers with higher private valuations tend to dominate the auction by paying higher prices for the shellfish before leaving the port early. In the final hour, only local primary processors with lower private values are present, and the price falls significantly. Prices can fluctuate a lot between the beginning and the end of auction sales. The two groups of bidders are clearly asymmetric. The impact on prices depends on the precise nature of the two distributions of private values and on their combination. The effect is presumably neutral in Le Guilvinec where the community of buyers has not changed since the ECAS, and is positive in Lorient after the collapse of the entry barrier to agents (mongers) with higher valuations. In the same respect, one may consider that the perception of risk has changed more significantly with the shift of the pairwise trading to an electronic Dutch auction system (due to the well-known winner’s curse effect), than with the simple transformation of the English shout auction into an electronic English auction system.

The bigger impact on average prices observed in Lorient is presumably more due to the substitution of auctioning for the pairwise trading organisation previously in force, than to electronics per se. Affiliation,
asymmetry and the perception of risk have simultaneously increased since the implementation of the new ECAS. In such circumstances a Dutch system produces higher prices than an English auction (Maskin and Riley 2000). The probability of winning the auction is highly affected by the implementation of a Dutch system: an English system would provide more information about other bidders’ private valuations. Interestingly, the introduction of the Euro represented a good opportunity for the implementation of electronic auction systems with support from harbour managers and with the assistance of European and regional subsidies. The introduction of the Euro seems to have been perceived differently in each place without affecting the average price in the two markets separately (otherwise, two break dates would have been found as the Bai-Perron procedure allows). The volatility of prices may have increased after the implementation of the Euro: managers interviewed reported irrational behaviour of bidders in the weeks following the introduction of the single currency, as though the Euro currency did not have the same value as French currency after conversion. This volatility was perhaps amplified by electronic-clock auction systems since the latter tend to exhibit higher prices with larger variation than direct sales on fish markets (Helstad et al. 2005: 310).

The underlying context is gradually to prepare the economic agents for the interconnection of fish markets on a regional or even wider scale. Although local, the new systems include a remote bidding access facility. The electronic system offers the potential to allow more remote bidders to participate.

2.3 Expected impact of remote bidding on fish prices

2.3.1 The remote access of bidders

Experiences abroad

The second aspect of widening markets is to attract newcomers in the system through the remote bidding access that Intranet and Internet systems may offer. In such systems, distant buyers can participate in the bidding process (Fig. 2.3). A distinction is made between local and remote systems, local and remote networks, internet and inter-connected systems like the Icelandic system where the sales are organised simul-
taneously by lots of a single species for all the domestic ports (Carleton 2000).

A major supplier of fish auction electronic systems in Europe offers five different types of equipment:

- Local auction system: electronic-clock system by a bid button or an advanced keyboard;
- Advanced sales room: individual PCs where the buyers can follow the sales, make their purchases and obtain various information such as supply and transaction data, average prices, statistics, etc.;
- Mobile auction systems: electronic auction clock mounted on a battery powered vehicle; buyers are equipped with portable transmitters;
- Auction networks: the products of each market connected to the network are sold simultaneously, which means that each market has to have one auction clock per market connected to the system. When the number of connected markets increases, this system is no longer feasible because the number of clocks cannot be seen simultaneously;
- Remote bidding system: it allows buyers to bid through terminals located in their homes or offices; the remote bidders receive exactly the same information as the buyers present in the auction room (supply and transaction data, sales results, statistics, etc.).

The introduction of remote auction systems presents the same heterogeneity in Europe as local computerised trading rooms. Some countries are more willing to adopt them than others. The first experience undertaken on the fish market was in Zeebrugge in 1987. This port had a strong advantage with its geographical position close to the biggest European markets (United Kingdom, France, Germany), but was limited by the low level of local landings, hence it looked for new suppliers and buyers. Around the year 2000, the company who intended to create a large interconnected European market for fish gave up this idea and remained a simple system supplier.

A remote bidding system was also introduced in Bergen (Norway) mainly because of the distance between the landing sites, the difficulties of using the road between the ports and the low domestic demand. Two important remote auction systems have been implemented: a sealed
Figure 2.3: A remote bidding system (Carleton 2000).
bid auction system for pelagic fish and an open English auction system (Armstrong 2001). Both are Intranet technologies and not viewing auction systems, the fish being sold at sea for pelagic catches. Both are auctions within a limited time.

Iceland presents an interesting case with respect to market interconnection. This country had no tradition of auction systems before the 1990s (landing sites scattered all along the coastline, bad road infrastructures). In 1987, the first attempt to link three fishing ports was undertaken and the network was computerised five years later (Arnarson and Trondsen 1998). The increase of prices was such that the network attracted newcomers into this English auction-type through a public address system (TENGILL). The local buyers raise a paddle showing their bid which is registered by a local operator who transfers remotely the information to a central shouting auctioneer visible to the buyers. In 1994, a second system (BODI), based on Dutch (and button) bidding this time through internet protocols, was implemented by two major market organisers who created a joint company (Islandmarkadur or ISM hf). The two systems attempted to merge in 1997 but without success (Graham 1999, p. 203). The Individual Transferable Quota (ITQ) system implemented in Iceland in 1984 has brought back to the national auction system Icelandic vessels which used to land abroad in Europe (because otherwise 25% of their fish quota would be withdrawn), but it did not out compete the contractual system fully (direct sales between fishermen and processors) despite higher prices because of the ITQ system and vertical integration between fishing and processing (Arnarson and Trondsen 1998).

**Remote bidding in France: a very recent development**

In France, the proportion of French fish auction markets authorising a remote access to their electronic bidding system reached 28% in 2007 (Fig. 2.4).

In a first step, remote bidding was circumscribed to the local buyers who can bid from their adjacent office through the computer network instead of inside the auction room. This small step towards a non-viewing auction has represented kind of a revolution for buyers who had always calculated their private valuation in front of the fish boxes where they can evaluate the gradation, quantity and quality of the fish. This has also imposed new constraints for the managers having to
Figure 2.4: Remote bidding access in the 40 French primary fish markets in 2007. Source: LEN-Corrail 2007.
improve and harmonise their gradation system in order to display the product characteristics on a catalogue before the sales.

2.3.2 Expected impact on prices

Theoretical and empirical insights

When it comes to electronic markets (e.g. through the Internet), the influence of other bidders could be even greater than in a local trading room. Even when agents can perfectly calculate the equilibrium of a game, they will not base their decisions on this calculus, but with respect to their expectations of the other players’ strategies (Kirman 1995). Expectations of others’ strategies might be different with an electronic system compared to a shout auction.

In particular, Internet technology has introduced asynchronies. The introduction of a time limit for bidding has resulted in “sniping” behaviour, i.e. people waiting for the final seconds to make a bid below their private value (Deveaux 2003). A limited time is applied in the two Norwegian auction fish markets above mentioned (Armstrong 2001). Sniping strategy cannot be adopted in the sealed bid envelope because the limited time leaves one hour to offer a single sealed bid. But the demersal fish is sold by ascending English auction within a limited time of a few hours, making this strategy possible. Comparable effects could be anticipated whenever remote bidders in “blind” conditions do face local buyers, creating asymmetry in the bidding process.

The perishable nature of fresh fish creates physical barriers to the extension of remote bidding systems. The logistics of fresh products, with higher asset specificity than ordinary products, is therefore more difficult to organise. Delivered products after remote purchase are frequently refused by buyers because the grade or quality of fish does not meet their expectations. This physical limit has been observed in other countries such as Iceland where logistic problems arise with the remote system with transportation costs of empty boxes sent back to their owners (Arnarson and Trondsen 1998). The freshness of the product matters a lot when selling the fish. The huge number of fish lots to be sold in a few hours makes the full market integration almost impossible, i.e. to organise sequentially and on a nationwide scale the sale of all products. The organisation and coordination costs to match supply and demand would be tremendous. The experience of Lorient where newcomers on both supply and demand sides shows these problems of
trading organisation since the sales period tends to be extended for one or two hours although prices fall throughout this period because the best bidders have left the auction. Usually, each auctioneer knows “his” buyers perfectly and organises the sales in connection with this knowledge, setting up the initial price for each lot as close as possible to the clearing price, for operators to save time. A good and qualified auctioneer can organise a great number of transactions in a very short amount of time. He loses information with an increasing number of remote bidders into the system.

**Some preliminary results from a survey of French auctioneers**

A quick survey completed by phone in June 2007 with a few auction market managers gave several intuitive answers and a general perception of remote bidding effects by their promoters. Six interviews were carried out with the auctioneers who created the most advanced system of remote bidding in France. One of them, currently the head of the French fish auctioneers’ association, launched in 1994 the third remote auction market in Europe and the first in France.

Most of the auction market managers are enthusiastic about the remote system and agree upon the positive effects it has had on prices. As an example, one of the auctioneers in La Rochelle reports at least two species (sea bass and squid; Fig. 2.5 a and b) for which prices have been significantly affected: “Before the implementation of the remote bidding system, we were facing regular marketing problems. Now the withdrawals have been reduced and prices are more consistent with other markets because two remote bidders from Brittany are interested in these products”. Supermarket buyers are now involved in the auction system and push all prices upwards. The auction manager in Roscoff, another squid marketplace authorising remote bidders since October 2005, also confessed that squid prices, since the introduction of remote bidding, have become “more coherent with the other marketplaces in France”.

Initially, the first project planned to set up auction networks between different market places but this occurred during the big market crisis of 1993-94 when the prices plummeted dramatically due to exceeding supply. With auction networks, the fear was great to accelerate the information of supply in excess and this system was abandoned for an individual remote access.

The underlying objective is to foster non-viewing purchase of fish in
order to prevent collusion among bidders. In that aspect, it has been successful, especially with a Dutch auction system. One auctioneer says: “When remote auctions were first introduced, local buyers were very few. 95% of the sales were coming from trawlers of 20 to 25 meters. They had a good pre-announcement system of catches. With the increasing market share of coastal fleets, this system is not so good and landings may fluctuate between 300 kilos and 10 tonnes without any announcement before the sales. It was then very easy for the dozen of bidders to set up collusive prices and to share the lots among them in a sort of playground atmosphere. With the introduction of two remote buyers only, this atmosphere has totally disappeared and more pressure has been put on the local buyers”. In this auction market, the market share of distant buyers is now greater than 60%.

New strategic behaviour can be observed because of remote bidding. Over time, local buyers end up getting to know which products are of interest for remote bidders. In one auction market with ascending bids, some local buyers push up the bids even though they are not interested in the products. Another auctioneer states this is a common practice between local buyers in the auction hall but it usually concerns buyers interested in the same lots. They may push up the bid intentionally to outcompete a rival on the downstream market in a “raising rivals’ costs” strategy. However, they become exposed to retaliation by the local rival. When it comes to distant buyers, the probability of retali-
ation is not so high. An auctioneer says: “I have a remote buyer who can alone increase the price of one species. However, the local buyers cannot push up the bidding process because auctions are descending and stop with the first bid”. Information is clearly asymmetric between local and distant buyers, to the extent that a phone line has been devoted to inform remote buyers before and during the sales in one market place, and the auction manager is even intending to add an audio link with the auctioneer through Internet during the auction. Beyond price levels, remote bidding has important restructuring effects for buyers. All auctioneers report a strong resistance from the local processors to prevent remote access. To be accepted, the remote system has been traded against a few concessions, like the arrival of additional fishing vessels in one of the auction markets, or a label policy to acknowledge the know-how of local processors in another. At least in three markets, some local buyers have bought a remote license, either to create an entry barrier when the number of licenses was limited, or to get a better accessibility to the auction system. In one of the markets, only 8 buyers remain in the trading room out of 25 available PCs. As an example of what the remote access offers, fishmongers who need to leave early the market place to open their shop can still participate remotely in the auction. One of the auction markets has been totally restructured after the implementation despite little effect on prices. Some 25 local processors used to bid for anchovy on behalf of Spanish buyers, taking a commission out of the sales. Just after the new access to auction through Internet, the Spaniards skipped over the local processors to buy the fish themselves. They finally worked together to enjoy economies of scale out for transportation and reduced the number of bidders to three or four. Since the closure of the anchovy fishery in the Bay of Biscaye in 2006, they left the market and both the trading room and the Internet auction system are no longer in use; local processors had to go back to former practices.

2.4 Conclusion and discussion

The results obtained in the first section are consistent with most of the empirical findings of the auction theory literature: the substitution of an auction market for the former pairwise trading organisation increases price levels (Bulow and Klemperer 1996, Arnarson and Trondsen 1998, Helstad et al. 2005). However, the results go a bit beyond that. In-
deed, in at least one of the two fish market places (Le Guilvinec), one should consider that the market institution has not basically changed because the ascending (English) auction system has been preserved. Nonetheless, the introduction of an electronic clock auction system has significantly modified the prices of fish (prawns) in levels (increased) and volatility (higher after the change). Regarding the relationship between the two French ports, rigorously selling identical products, a better price integration has been achieved after the implementation, but the price volatility has also significantly increased since then. Part of this outcome may result from the introduction of the Euro (1st January 2002) because the buyers’ behaviours were reported by auctioneers as being irrational just after the introduction of the single currency. Nevertheless, the decreasing control over price setting mechanisms by the auctioneer with the electronic system instead of the former shout auction can also be influential.

The adoption of new information technology in market organisation can be viewed as deterministic. In that view, technological change causes social and economic changes, as if it was elaborated outside any social influence. Other authors prefer “to understand the process by which a network is constructed by enrolling social and material elements” (Callon 1986), i.e. how do the social groups involved in the innovating process interact through their power relationships. Technology and the social network are not separate elements, and the former is certainly not the output of the latter.

Remote bidding access allowed by electronic means represents a step forward in the “framing process” to get closer to the economists’ view of what a market should be (and not of what they are): a centralised system with anonymous transactions among bidders (Garcia 1986, Callon 1998). If auctioning is a progress as compared to pairwise trading, a non-viewing remote auction system is even more desirable for economists, whose influence on market framing is not studied enough. However, this new framework may not represent the ultimate lock-in solution as opportunistic strategies arise and may address new questions to auction theory. A limited period of time for auctioning like in Norway provides opportunities for sniping behaviour for remote bidders who may then bid at the ultimate moment under their private valuation. Hypothetically, the accuracy and instantaneity of clock timing using a computer makes a difference with a shout auction. In the case of ascending auction and because of asymmetry between local and remote buyers who are not necessarily interested in the same fish lots, a strategic behaviour may
increase the winner’s curse for remote bidders pushed up in the auction by local traders who want to “punish” the outsiders. We believe that the introduction of electronic remote access gives new opportunities for research within the field of auction theory: this paper simply indicates clear empirical evidence of higher prices resulting from electronic auction system and possibly from remote bidding access. A further look at these new trading systems would consider their influence in terms of re-structuring the buyers-sellers relationships and the social networks of markets.
<table>
<thead>
<tr>
<th>Port</th>
<th>Date</th>
<th>No.</th>
<th>Remote buyers</th>
<th>Observations</th>
</tr>
</thead>
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<tr>
<td>La Turballe</td>
<td>Jan 2002</td>
<td>5</td>
<td>Remote bidding through Internet for pelagic fish (anchovy, horse mackerel). Implemented by PEFA (Zeebrugge).</td>
<td></td>
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<td>Lesconil</td>
<td>Apr 2002</td>
<td>3</td>
<td>Remote access for 3 buyers of a neighbour auction market.</td>
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<tr>
<td>La Rochelle</td>
<td>Nov 2004</td>
<td>22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oléron</td>
<td>Apr 2005</td>
<td>6</td>
<td>Implementation cost = 250 Eur + 78 Eur/month.</td>
<td></td>
</tr>
<tr>
<td>Roscoff</td>
<td>Oct 2005</td>
<td>53</td>
<td>19 remote buyers initially; 53 in June 2007 weighing 53% of the sales tonnage; more boats have joined the auction (waiting list) to level out supply and demand.</td>
<td></td>
</tr>
<tr>
<td>Grandcamp</td>
<td>2005</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Port-en-Bessin</td>
<td>2005</td>
<td>15</td>
<td>Firstly implemented in Sep 1994, 3 months after Cherbourg. An auction network was even envisaged at that time.</td>
<td></td>
</tr>
<tr>
<td>Granville</td>
<td>2005</td>
<td>10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Saint-Quay Portrieux</td>
<td>Oct 2006</td>
<td>38</td>
<td>Of the 38 lines opened in 2006 only some 15 regular and major buyers remain. Of the 38 lines opened in 2006 only some 15 regular and major buyers remain. Fee = 40 Eur/month + condition of assiduity.</td>
<td></td>
</tr>
<tr>
<td>Erquy</td>
<td>Oct 2006</td>
<td>38</td>
<td>Fee = 40 Eur/month</td>
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<td>Quiberon</td>
<td>Jan 2006</td>
<td>11</td>
<td>Fee = 67 Eur/month</td>
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<tr>
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<td>18 Jun 2007</td>
<td>0</td>
<td></td>
<td></td>
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<td>Fécamp</td>
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<td>5</td>
<td>Auction network with Fécamp. 5 buyers from Dieppe are now connected. Fécamp network began in Sep 1994, 3 months after Cherbourg. An auction network was even envisaged at that time.</td>
<td></td>
</tr>
<tr>
<td>Audierne</td>
<td>7 Jul 2007</td>
<td>15</td>
<td>Managed by CCI Quimper; pilot-experience for the 6 other markets. In 1999, 2 months after Cherbourg, the auction network was even envisaged at that time.</td>
<td></td>
</tr>
<tr>
<td>Le Guilvinec</td>
<td>Sep 2007</td>
<td>2</td>
<td>Managed by CCI Quimper; pilot-experience for the 6 other markets. In 1999, 2 months after Cherbourg, the auction network was even envisaged at that time.</td>
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<td>Loctudy</td>
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<td>Concarneau</td>
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<td>1</td>
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<td>Royan</td>
<td>Oct 2007</td>
<td>25</td>
<td>Contact has been taken with Quiberon.</td>
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Appendix
Table 2.3: Bai-Perron procedure for the model with $Pl$ as the dependent variable.

LWZ: Liu, Wu and Zidek. BIC: Bayesian information criterion. *: significance at the 5% level.

<table>
<thead>
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<th>$Z_t = { 1 }$</th>
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<td></td>
<td>41.99*</td>
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<td>$SupF(3) 2$</td>
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<th>BIC</th>
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<td>1</td>
<td>2</td>
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<td></td>
<td>0.03</td>
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*Serial correlation in the disturbances is not allowed because lagged dependent variables are included as regressors. The residuals are pre-whitened using an AR(1).

*The significance level used for the sequential procedure is equal to 5%
Table 2.4: Bai-Perron procedure for the model with $P_g$ as the dependent variable.

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<td>$P_g$</td>
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<td>$P_g^t - 1, SD_1, ... , SD_{51}$</td>
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Tests

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<td>(2</td>
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<td>6.71</td>
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Number of breaks selected

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Dates of breaks (sequential procedure)

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Ljung-Box tests for serial correlation

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<td>LB</td>
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Notes:

- Serial correlation in the disturbances is not allowed because lagged dependent variables are included as regressors. The residuals are pre-whitened using an AR(1).
- The significance level used for the sequential procedure is equal to 5%.

LWZ: Liu, Wu and Zidek. BIC: Bayesian information criterion.

Specifications

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<th>$\phi = 2$</th>
<th>$d = 0.15$</th>
<th>$\sigma = 0.1$</th>
<th>$a = 0.1$</th>
<th>$b = 0.1$</th>
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</thead>
<tbody>
<tr>
<td>$\epsilon$</td>
<td>$z = c$</td>
<td>$z = c$</td>
<td>${z_d = d}$</td>
<td>${z_d = d}$</td>
<td>${z_d = d}$</td>
<td>${z_d = d}$</td>
</tr>
</tbody>
</table>

Table 2.4: Bai-Perron procedure for the model with $P_g$ as the dependent variable.

- *Significance at the 5% level.
Table 2.5: Bai-Perron procedure for the first equation of the VAR model.

LWZ: Liu, Wu and Zidek. BIC: Bayesian information criterion. *: significance at the 5% level.

<table>
<thead>
<tr>
<th>Specifications</th>
<th>Tests</th>
<th>Number of breaks selected</th>
<th>Dates of breaks (sequential procedure)</th>
<th>Ljung-Box tests for serial correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Y_t = {P_t}$</td>
<td>$SupF_T(1)$</td>
<td>Sequential</td>
<td>Date</td>
<td>$LB(1)$</td>
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<td>$Z_t = {1}$</td>
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<td>LWZ</td>
<td>2001:44</td>
<td>0.01</td>
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<tr>
<td>$X_t = {P_{t-1}, \ldots, P_{t-3}, P_{y_{t-1}}, \ldots, P_{y_{t-3}}, SD_1, \ldots, SD_{51}}$</td>
<td>$SupF_T(3)$</td>
<td>BIC</td>
<td>2002:15</td>
<td>33.21</td>
</tr>
<tr>
<td>$q = 1$</td>
<td>$UD_{max}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p = 57$</td>
<td>$WD_{max}(5%)$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$M = 3$</td>
<td>$h = 38$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\epsilon = 0.15$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Tests: $SupF_T(n)$

| $SupF_T(1)$ | $SupF_T(2)$ | $SupF_T(3)$ | $UD_{max}$ | $WD_{max}(5\%)$ |
| 27.41* | 18.81* | 12.75* | 27.41* | 27.41* |

Number of breaks selected: Sequential 1, LWZ 1, BIC 2


Ljung-Box tests for serial correlation:

- $LB(1)$
- $LB(26)$
- $LB(52)$

*Serial correlation in the disturbances is not allowed because lagged dependent variables are included as regressors. The residuals are pre-whitened using an AR(1).

*The significance level used for the sequential procedure is equal to 5%.
Table 2.6: Bai-Perron procedure for the second equation of the VAR model.

Specifications

<table>
<thead>
<tr>
<th>Variables</th>
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<td>$Y_t$</td>
<td>${P_{g_t}}$</td>
</tr>
<tr>
<td>$Z_t$</td>
<td>${1}$</td>
</tr>
<tr>
<td>$X_t$</td>
<td>${P_{l_t-1},...,P_{l_t-3},P_{g_t-1},...,M=3,\epsilon=0.15, P_{g_t-3},SD_1,...,SD_{51}}$</td>
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Tests

<table>
<thead>
<tr>
<th>Test</th>
<th>SupF$\left(T^{(1)}\right)$</th>
<th>SupF$\left(T^{(2)}\right)$</th>
<th>SupF$\left(T^{(3)}\right)$</th>
<th>UDmax</th>
<th>WDmax</th>
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</thead>
<tbody>
<tr>
<td>0.05% CI</td>
<td>10.08*</td>
<td>8.66*</td>
<td>7.24*</td>
<td>10.08*</td>
<td>10.43*</td>
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</tbody>
</table>

Dates of breaks (sequential procedure)

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</thead>
<tbody>
<tr>
<td>Date</td>
<td>2002:16</td>
</tr>
</tbody>
</table>

95% c.i.

<table>
<thead>
<tr>
<th>Breaks Selected</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>95% c.i.</td>
<td>2001:36 2002:36</td>
</tr>
</tbody>
</table>

Ljung-Box tests for serial correlation

| Test | SupF$\left(T^{(2|1)}\right)$ | SupF$\left(T^{(3|2)}\right)$ |
|------|-----------------------------|-----------------------------|
| 5.93 | 2.78                        |                             |

Serial correlation in the disturbances is not allowed because lagged dependent variables are included as regressors. The residuals are pre-whitened using an AR(1).

The significance level used for the sequential procedure is equal to 5%.

<table>
<thead>
<tr>
<th>Breaks Selected</th>
<th>Sequential</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>2002:16</td>
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</table>

95% c.i.

<table>
<thead>
<tr>
<th>Breaks Selected</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>95% c.i.</td>
<td>2001:36 2002:36</td>
</tr>
</tbody>
</table>

The significance level used for the sequential procedure is equal to 5%.

Specifications

<table>
<thead>
<tr>
<th>Specifications</th>
<th>${1}$</th>
<th>${D_{S_1-d},...,D_{S_1-d_{-6}}, d_{-1}}$</th>
<th>${1}$</th>
<th>${D_{g_{-1}}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma = 0.15$</td>
<td>$\epsilon = b$</td>
<td>$\gamma = d$</td>
<td>$\gamma = d_{-1}$</td>
<td>$\gamma = \gamma_{g_{-1}}$</td>
</tr>
</tbody>
</table>
When a supply and demand model is recursive, with errors uncorrelated across the two equations, ordinary least squares (OLS) is the recommended estimation procedure. Supply to a daily fish market is determined by the previous night’s catch, so this would appear to be a good example of a recursive market. Despite this, data from the Fulton fish market are treated in the literature, without explanation, as coming from a simultaneous-equations market. We provide the missing explanation: inventory changes, influenced by current price, affect daily supply. Instrumental variable estimates using the full data set differ very little from OLS estimates using only observations with little inventory change, providing strong support for our explanation. Finally, we note that because of inventory changes, estimates of supply price elasticities in high-frequency markets must be interpreted with care.

3.1 Introduction

It is well-known that a recursive equation system can be estimated unbiasedly using ordinary least squares (OLS), so long as errors are uncorrelated across equations. Greene (2003, p.411) has a good exposition. In light of this, researchers should be eager to take advantage of any situation in which a simultaneous equation model can be formulated as a recursive system. Doing so would rationalize the use of OLS,
avoiding the small-sample bias and loss of precision inherent in alternative instrumental variable (IV) procedures. In this paper we look at the simplest simultaneous equation system, a supply and demand model, and ask under what circumstances it would be legitimate to model it as a recursive system.

We were motivated by data from the Fulton fish market. In this daily market, supply is determined by the catch the night before, so that it looks to be a prime candidate for modeling supply and demand as a recursive market. Yet, papers in the literature using these data, including Graddy (1995), Angrist, Graddy, and Imbens (2000), Chernozhukov and Hansen (2001), Lee (2004) and Graddy (2006), estimate using instrumental variables, with little explanation for why a recursive model is not appropriate, beyond cursory statements such as “Because quantity sold and price are endogenous ...” (Graddy, 1995, p.86). Further, econometrics textbooks have been using these data for illustrations and in assignments, also without explaining why they can be viewed as representing simultaneous determination of price and quantity. One textbook, Murray (2006, p.604), even goes so far as to state that these studies “typify simultaneous supply and demand studies.”

In this paper we offer an explanation of why a recursive model is not appropriate for the Fulton fish market data, and indeed is not appropriate for any high-frequency market in which buffer stocks play an active role. The essence of our explanation is as follows. If the quantity supplied can be affected by inventory depletions or additions, even if inventory can only be held for a short amount of time, as in the case of fish, current price can affect vendors’ decisions about how much supply to make available on the market. The data provide strong support for this explanation. Instrumental variable estimates using the full data set differ very little from OLS estimates using only observations with little inventory change. A second contribution of this paper is to note that if vendors do behave in this fashion, estimates of supply price elasticities require careful interpretation.

3.2 Literature review

The literature on this issue begins with Wold (1954) who argues that multi-agent models are necessarily recursive rather than simultaneous because it takes time for agents to respond to their environments. The modern simultaneous equations literature pays only lip service to Wold,
however. Hausman (1983, p.402), for example, simply states that the recursive model, in conjunction with uncorrelated errors, “seems unacceptable in most model specifications”, but offers neither an explanation of this view nor an example of a market that would satisfy the assumptions of the recursive model.

Rothenberg (1990, p.231-2) is an exception, offering an explanation for why the Wold view is ignored: “When time is explicitly introduced into the model, simultaneity disappears and the equations have simple causal interpretations. But, if response time is short and the available data are averages over a long period, excess demand may be close to zero for the available data. The static model with its simultaneity may be viewed as a limiting case, approximating a considerably more complex dynamic world. This interpretation of simultaneity as a limiting approximation is implicit in much of the applied literature and is developed formally in Strotz (1960)”.

From this it seems that a crucial characteristic of data that renders them eligible for recursive modeling is the frequency of observations. Darnell (1994, p.346), for example, writes “Institutional realities may deny feedback and allow only one-way causal chains if the frequency of the data is high. If, for example, daily data are available on some variables it may be quite reasonable to impose a hierarchical causal chain, but if the data are monthly the strict hierarchy may be subsumed within the data and will appear, then, as simultaneous determination of the variables via feedback with all the commensurate identification and estimation issues that affect simultaneous models.”

Here is how the Strotz/Rothenberg/Darnell argument would apply to the Fulton fish market data. Suppose that on a daily basis the fish market is recursive because fish caught last night determine today’s supply and so supply is unaffected by current price. But suppose that today’s price serves as tomorrow’s expected price. If the fish market data were monthly, the monthly price in the data would be an average. In a month with a high average price we would expect fishermen, as they experience higher prices during the course of the month, to react by fishing more intensively and so catch more fish. There would be simultaneity in the monthly data despite no simultaneity in the daily data.

In summary, this literature explains why weekly or monthly data are characterized by simultaneity, but leaves open the question of how to model with high-frequency data such as daily data. A reader is left with the impression that for the case of high-frequency data a recursive
model is appropriate unless explicitly argued to the contrary. But no hint is provided for how a high-frequency market could exhibit simultaneity. One purpose of this paper is to supplement this literature by presenting an argument for why any high-frequency data from a market with inventories must be modeled as simultaneous, not recursive.

A natural place to look for information on this issue is the textbook literature. Simultaneity is one of the original reasons for why econometrics was developed as a separate branch of statistics, a consequence of which is that most textbooks contain a chapter on simultaneous equations. Only about a quarter of the forty textbooks we looked at discuss recursive systems, however, and of those that do, no explicit examples of recursive supply and demand markets are offered. One or two texts mention that agricultural markets might be recursive. Pindyck and Rubinfeld (1998, p.348), for example, state “In the supply equation the quantity supplied depends only on the price level in the previous year (as one might expect with farm products).” That this is not a good example is illustrated very clearly by Suits (1955), the first study to apply simultaneous equations estimation procedures to supply and demand. Suits recognizes that potential supply is determined in the watermelon market by plantings made long before the watermelons are brought to market, and so cannot be affected by current watermelon price. But he notes that current price will determine how many of the watermelons in the field will actually be brought to market, and so there is simultaneity after all. Murray (2006, p.613) has a nice textbook exposition. This example illustrates that reasons for simultaneity may be more subtle than the textbook literature would have us believe.

3.3 Simultaneous equations with buffer stocks

The essence of our explanation for why the Fulton fish market suffers from simultaneous equation bias is that supply in this market is influenced by inventory changes. The quantity “supplied” to this market is last night’s catch minus an inventory change. It seems reasonable to expect that if the market price on a particular day is abnormally low, an agent may choose not to sell all of last night’s catch on today’s market, bumping up his inventory in the hope that tomorrow’s price might be better. (Indeed, based on weather forecasts he may have good reason to believe that tomorrow’s price will be better, or worse.) If the market price on a given day is abnormally high, an agent may choose to aug-
ment last night’s catch with inventory he has left from the previous day. In this way current price affects the supply offered on the market and creates the simultaneity assumed by the literature using these data. Here is a simple model to illustrate this phenomenon. $Q_t$, supply on day $t$, is given by the previous night catch less day $t$’s change in inventory. We model the previous night catch as $\alpha + \eta W_{t-1} + u_{t-1}$ where $W_{t-1}$ is the previous night weather and $u_{t-1}$ is a traditional error term. We model the change in inventory as $\theta(P_n - P_t) + v_t$ where $P_n$ is the normal price (or, alternatively, the next day’s anticipated price), $P_t$ is price on day $t$, and $v_t$ is an error. All this gives rise to the following supply function:

$$Q_t = \alpha + \eta W_{t-1} - \theta(P_n - P_t) + u_{t-1} - v_t \quad (3.1)$$

The demand for fish on day $t$ is given by the inverse demand function

$$P_t = \gamma + \delta Q_t + \epsilon_t \quad (3.2)$$

where $\epsilon_t$ is a traditional error term and we have incorporated the equilibrium condition that quantity demanded equals quantity supplied. If $\theta$ is zero or if in every period $P_n$ matched $P_t$, inventory change would be given by $v_t$, a scenario we describe as “inventory change close to zero” or “no inventory change.” In this situation we would have the recursive system

$$Q_t = \alpha + \eta W_{t-1} + u_{t-1} - v_t \quad (3.3)$$

$$P_t = \gamma + \delta Q_t + \epsilon_t \quad (3.4)$$

For OLS to be unbiased for estimation of this recursive system $\epsilon_t$ must be uncorrelated with $u_{t-1}$ and $v_t$. It seems safe to assume that $\epsilon_t$ and $u_{t-1}$ are uncorrelated; there is no good reason why the error associated with the previous night’s catch should influence the error in today’s demand. Assuming that $\epsilon_t$ and $v_t$ are uncorrelated is more problematic. A particularly strong demand (a high $\epsilon_t$) might cause inventories to be fully depleted according to the $(P_n - P_t)$ specification, in which case $v_t$ would need to be positive (because inventories cannot be negative), generating a positive correlation between $\epsilon_t$ and $v_t$. When inventory change is close to zero (i.e., when we have a recursive system) this correlation is
unlikely because it is only triggered by large positive values of $\epsilon_t$ which fully deplete inventories.

The main consequence of all this is that the recursive system given by Eq. 3.3 and 3.4 does not suffer from simultaneous equations bias. Eq. 3.3 can be estimated unbiasedly by regressing $Q_t$ on $W_{t-1}$ using OLS, and Eq. 3.4 can be estimated unbiasedly by regressing $P_t$ on $Q_t$ using OLS.

But if inventory change is affected by $P_t$, as modeled in Eq. 3.1, then simultaneity appears. An increase in $t$ increases directly $P_t$ from Eq. 3.2, but this increase in $P_t$ affects $Q_t$ from Eq. 3.1, so the Eq. 3.2 error $\epsilon_t$ and regressor $Q_t$ are correlated. This creates simultaneous equation bias using OLS. Eq. 3.2 must be estimated using an IV procedure. This conclusion is strengthened by considering possible correlation between $\epsilon_t$ and $v_t$.

An implication of the above explanation is that whenever inventory change is “close to zero” there is little or no simultaneity in the data; in this case we know that $P_t$ has had little or no impact on $Q_t$ because any such impact is entirely through inventory change. Consequently, if we were to pick out those observations without substantive inventory change and estimate using OLS using just these observations, we should produce a demand elasticity estimate comparable to that produced by using IV with all the data. Doing this for the Fulton fish data should serve as an empirical check on the role of inventory change creating simultaneity in this market, through a model as described above. We report on this later.

This is a generic explanation for simultaneity; it applies to any high-frequency market in which sellers influence supply by adjusting inventories in response to price changes. One implication of this, as already noted, is that what appear to be recursive markets are not in fact recursive insofar as estimation is concerned. A second implication, to which we now turn, is that new meaning needs to be attached to estimates of the price elasticity of supply in such models.

### 3.4 Interpreting supply curve estimates

The traditional interpretation of the supply curve is that it tells us how a producer changes output in response to a price change. If we now recognize that the quantity sold on a market is not necessarily what is produced during the period, but rather embodies inventory
changes, the slope on the quantity variable reflects two types of quantity changes in response to price changes. Now suppose that the seller in this market, who may or may not be the producer, exploits price changes by adjusting inventories according to

$$\Delta_{\text{inventory}} = \theta (P_n - P)$$  \hspace{1cm} (3.5)

where $P_n$ is the "normal" price, for example a long-run average. (It could alternatively be whatever price is expected to prevail tomorrow.) Now the actual supply in this market becomes

$$S_{\text{actual}} = \kappa + \lambda P - \theta (P_n - P) = \kappa^* + (\lambda + \theta) P$$ \hspace{1cm} (3.6)

Estimation using traditional simultaneous equation estimation techniques produces an asymptotically unbiased estimate of $\lambda + \theta$, not an estimate of $\lambda$. In some contexts, in which short-run behavior is of interest, this may be what we want. But in other contexts, in which longer-run reactions to a permanent change in price are of interest, this is not estimating what we want to estimate.

This problem does not characterize markets in which available data are averages over longer time periods because over these time periods inventory changes would be mostly averaged away. To the best of our knowledge, this phenomenon is not recognized in the literature.

In imperfectly competitive markets, the interpretation of the supply curve (which is now a pricing curve) will be different. In this case, fish vendors could be manipulating inventories in order to set prices, so that the causation goes from inventory change to price change rather than from price change to inventory change as argued earlier. Indeed, empirical regularities in the data suggest that inventories are playing a very active role in the supply side of this market. Increases (decreases) in inventories above (below) the norm cause vendors to increase (decrease) supply by drawing down (building up) inventories, but not by as much as the initial inventory change. And fishers as well as vendors are affected by inventory levels; when inventory is high (low) a smaller (larger) amount of fish tends to be delivered.\footnote{Despite these empirical regularities we were unable successfully to estimate the precise role of inventory change; all models did not survive a sensitivity analysis. These data are not able to speak loudly about the supply side of this market except to say that inventories play a major role.} Nonetheless, the earlier logic regarding simultaneity holds. An increase in the demand error term will have an effect on the firm’s pricing equation (and thus
quantity supplied) through manipulation of inventories: the demand error term and quantity will be correlated. Furthermore, small inventory change would continue to correspond to a situation in which there is little simultaneity.

3.5 The Fulton fish market data

Graddy (2006) provides a very good description of the Fulton fish market data. These are 111 daily observations on price and quantity of whiting in 1991-2, along with weather information serving as instrumental variables. The instrumental variable “stormy” is a dummy variable constructed from moving averages of the previous three days’ wind speed and wave height (before the trading day). Stormy indicates wave height greater than 4.5 feet and wind speed greater than 18 knots. A second instrumental variable, “mixed” is a dummy variable constructed in similar fashion, representing days with severe weather, but less severe than “stormy” days. Mixed indicates wave height greater than 3.8 feet and wind speed greater than 13 knots when Stormy equals zero.

The data were aggregated from information on quantity sold and price each day to each customer. There are two complications with the data. First, not all buyers pay the same price per pound of whiting. We ignore this complication and assume that all buyers pay the same price, measured as the average of individual transactions prices weighted by quantities sold. Secondly, the data refer to one of six agents selling whiting in this market. We assume that this dealer’s market share was constant during the period, so that we can analyse his quantities as if they were market quantities. Making these kinds of assumptions using economic data is commonplace, reflecting Kennedy’s (2002) eighth commandment of applied econometrics: Thou shalt be willing to compromise.

If whiting were extremely perishable, last night’s catch would all have to be sold today, and this would be a recursive market. But, whiting stays sufficiently fresh to sell for at most four days after it is received, although it is usually sold the day it is received or the day after. On 54% of the days, total quantity sold exceeds total quantity received. Furthermore, the mean daily total quantity sold is less than the mean total quantity received by 92 pounds (the standard deviation is equal to 3,024 pounds), or by 1.4% of the quantity sold. This amount is likely to be unrecorded sales or shrinkage. During this period inventories never
fell to zero, nor rose to a level that could not be accommodated, so there are no limit problems with these data. Average daily fish sales during this period were 6300 pounds, with an average absolute value of daily inventory change of 2500 pounds. Despite the perishable nature of this product, average inventory holdings were more than 2000 pounds higher than average daily sales.

These figures are all consistent with our story that inventories are playing an important role in this market. The main implication of this additional information is that the recorded quantity of whiting sold each day does not necessarily equal the quantity caught the night before. Furthermore, in equilibrium, one would expect the mean quantity received to be slightly more (by 92 pounds) than the mean recorded quantity sold in order to allow for unrecorded sales and shrinkage.

Figure 3.1 plots the daily difference between the total quantity received and the total quantity sold, adjusted by 92 pounds each day for unrecorded sales and shrinkage. As is evident, the daily difference is quite variable. The big upward spike took place on Friday, March 13, during Lent, when an unusually large quantity of fish was received. Sales on Friday were relatively smaller than on previous Fridays, which appeared to continue throughout Lent. On the following Monday, the day of the large negative spike, very little fish was received, and most fish was sold from inventory.\footnote{Overall during Lent, more fish was both received and sold than at other times, with Mondays and Thursdays being especially big days. This is consistent with what would be expected (see Bell 1968).}

For the purposes of our estimation below, we define days in which inventory change is “close to zero” in the following somewhat arbitrary fashion. We estimated the standard error of daily inventory changes (3021 pounds) and used it to calculate the standard error (287 pounds) of the average of the daily inventory changes. Any day during which inventories changed by less than twice this latter standard error was considered to be a day of “close to zero inventory change” or “no inventory change”. This gave rise to 34 “no inventory change” days, and 77 days with substantive inventory change. Further, we divided the subsample of inventory change days into days in which the inventory changes were positive, and days in which the changes were negative. In Table 3.1 below we present summary statistics for the full samples and subsamples.

As can be seen from the table, there are no significant differences in
Figure 3.1: Daily difference in total quantity received and total quantity sold.
Table 3.1: Summary statistics.

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>No change</th>
<th>Change</th>
<th>Depletions</th>
<th>Additions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>s.d.</td>
<td>mean</td>
<td>s.d.</td>
<td>mean</td>
</tr>
<tr>
<td></td>
<td>t-test p-value</td>
<td></td>
<td>t-test p-value</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Price</td>
<td>0.88 (0.34)</td>
<td>0.95 (0.31)</td>
<td>0.86 (0.34)</td>
<td>0.19</td>
<td>0.84 (0.36)</td>
</tr>
<tr>
<td>Qty sold</td>
<td>6425 (4040)</td>
<td>5685 (3988)</td>
<td>6621 (4093)</td>
<td>0.26</td>
<td>5749 (3540)</td>
</tr>
<tr>
<td>Qty received</td>
<td>6427 (4981)</td>
<td>5783 (3976)</td>
<td>6711 (5364)</td>
<td>0.37</td>
<td>3356 (2839)</td>
</tr>
<tr>
<td>Stormy</td>
<td>0.29 (0.46)</td>
<td>0.18 (0.39)</td>
<td>0.34 (0.48)</td>
<td>0.09</td>
<td>0.38 (0.29)</td>
</tr>
<tr>
<td>Mixed</td>
<td>0.31 (0.46)</td>
<td>0.44 (0.50)</td>
<td>0.25 (0.43)</td>
<td>0.04</td>
<td>0.24 (0.43)</td>
</tr>
<tr>
<td>Monday</td>
<td>0.19 (0.39)</td>
<td>0.12 (0.33)</td>
<td>0.22 (0.42)</td>
<td>0.20</td>
<td>0.14 (0.35)</td>
</tr>
<tr>
<td>Tuesday</td>
<td>0.21 (0.41)</td>
<td>0.18 (0.38)</td>
<td>0.22 (0.42)</td>
<td>0.60</td>
<td>0.30 (0.36)</td>
</tr>
<tr>
<td>Wednesday</td>
<td>0.19 (0.39)</td>
<td>0.21 (0.41)</td>
<td>0.18 (0.39)</td>
<td>0.77</td>
<td>0.11 (0.31)</td>
</tr>
<tr>
<td>Thursday</td>
<td>0.21 (0.41)</td>
<td>0.24 (0.43)</td>
<td>0.19 (0.40)</td>
<td>0.63</td>
<td>0.27 (0.45)</td>
</tr>
<tr>
<td>Friday</td>
<td>0.21 (0.41)</td>
<td>0.26 (0.45)</td>
<td>0.18 (0.39)</td>
<td>0.33</td>
<td>0.19 (0.30)</td>
</tr>
<tr>
<td>Cold</td>
<td>0.50 (0.50)</td>
<td>0.41 (0.50)</td>
<td>0.15 (0.50)</td>
<td>0.41</td>
<td>0.51 (0.51)</td>
</tr>
<tr>
<td>Rainy</td>
<td>0.16 (0.37)</td>
<td>0.21 (0.41)</td>
<td>0.14 (0.35)</td>
<td>0.20</td>
<td>0.16 (0.37)</td>
</tr>
</tbody>
</table>

Observations | 111 | 34 | 77 | 37 | 40
prices in inventory depletion or inventory addition days, than from other days. This result carries through if we divide the full sample into days in which the inventory change is greater than zero and days in which it is less than zero, or if we divide the full sample into days in which the inventory change is greater than or less than 92. Prices are similar on these days because inventory adjustment behaviour is in essence cushioning price changes, concealing the relationship between price and inventory adjustment. The only statistically significant differences in the subsamples regarding price and quantity are that the quantity received is significantly larger on days in which there are inventory additions rather than depletions, consistent with the story we are telling.

3.6 Estimation with the Fulton fish market data

The supply curve for the Fulton fish market is not identified, so we cannot look at that side of the market. On the demand side, the demand equation can be written as

$$\ln q^d_t(p) = \beta_0 + \beta_1 \ln(p) + \beta_2 x + \epsilon^d_t$$  \hspace{1cm} (3.7)

where the $x$ are exogenous dummy variables representing days of the week and the weather onshore. Table 3.2 presents estimates of this equation. The IV estimates result from using the variable “stormy” as an instrument and the variables “stormy” and “mixed” as instruments. When using all the data, as reported in columns 1 through 3 of Table 3.2, the IV estimates of the price elasticity of demand contrast sharply with the ordinary least squares estimates. Together with the small $p$-value for the Hausman test statistic, this suggests that there is considerable simultaneity in these data.

As explained earlier, we have reason to believe that OLS should exhibit very little simultaneity bias if it is applied using only observations for which inventory changes are small. To investigate this we separated the data into days in which the inventory change is close to zero (the “no change” data), as described earlier, and days in which the inventory change is substantive.

The results in Table 3.2 are striking. In the regressions using only the data with inventory changes, the $p$-value for the Hausman test drops
Table 3.2: OLS and IV regressions and covariates. Standard errors in parentheses; boldface type indicates significance at the 5% level.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
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<th>8</th>
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<tbody>
<tr>
<td>Dependent variable: quantity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>Full sample</td>
<td>OLS</td>
<td>IV</td>
<td>IV</td>
<td>OLS</td>
<td>IV</td>
<td>IV</td>
<td>OLS</td>
<td>IV</td>
<td>IV</td>
</tr>
<tr>
<td>stormy</td>
<td>-0.545</td>
<td>-1.223</td>
<td>-0.947</td>
<td>-0.422</td>
<td>-1.137</td>
<td>-0.892</td>
<td>-0.958</td>
<td>-0.97</td>
<td>-1.233</td>
</tr>
<tr>
<td>stormy/mixed</td>
<td>(0.175)</td>
<td>(0.532)</td>
<td>(0.410)</td>
<td>(0.185)</td>
<td>(0.425)</td>
<td>(0.380)</td>
<td>(0.451)</td>
<td>(3.789)</td>
<td>(1.133)</td>
</tr>
<tr>
<td>day1</td>
<td>0.032</td>
<td>-0.033</td>
<td>-0.007</td>
<td>0.286</td>
<td>0.284</td>
<td>0.284</td>
<td>-0.748</td>
<td>-0.75</td>
<td>-0.785</td>
</tr>
<tr>
<td></td>
<td>(0.207)</td>
<td>(0.226)</td>
<td>(0.215)</td>
<td>(0.219)</td>
<td>(0.241)</td>
<td>(0.229)</td>
<td>(0.513)</td>
<td>(0.720)</td>
<td>(0.535)</td>
</tr>
<tr>
<td>day2</td>
<td>-0.493</td>
<td>-0.533</td>
<td>-0.517</td>
<td>-0.362</td>
<td>-0.38</td>
<td>-0.374</td>
<td>-0.789</td>
<td>-0.789</td>
<td>-0.788</td>
</tr>
<tr>
<td></td>
<td>(0.204)</td>
<td>(0.220)</td>
<td>(0.210)</td>
<td>(0.224)</td>
<td>(0.247)</td>
<td>(0.235)</td>
<td>(0.427)</td>
<td>(0.427)</td>
<td>(0.430)</td>
</tr>
<tr>
<td>day3</td>
<td>-0.539</td>
<td>-0.576</td>
<td>-0.561</td>
<td>-0.413</td>
<td>-0.39</td>
<td>-0.398</td>
<td>-0.892</td>
<td>-0.894</td>
<td>-0.942</td>
</tr>
<tr>
<td></td>
<td>(0.206)</td>
<td>(0.222)</td>
<td>(0.212)</td>
<td>(0.232)</td>
<td>(0.256)</td>
<td>(0.243)</td>
<td>(0.414)</td>
<td>(0.793)</td>
<td>(0.457)</td>
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<tr>
<td>day4</td>
<td>0.095</td>
<td>0.118</td>
<td>0.108</td>
<td>0.255</td>
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<td>-0.401</td>
<td>-0.404</td>
<td>-0.461</td>
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<tr>
<td></td>
<td>(0.201)</td>
<td>(0.216)</td>
<td>(0.207)</td>
<td>(0.233)</td>
<td>(0.265)</td>
<td>(0.250)</td>
<td>(0.403)</td>
<td>(0.913)</td>
<td>(0.465)</td>
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<tr>
<td>cold</td>
<td>-0.062</td>
<td>0.068</td>
<td>0.015</td>
<td>-0.029</td>
<td>0.135</td>
<td>0.079</td>
<td>-0.194</td>
<td>-0.193</td>
<td>-0.166</td>
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<tr>
<td></td>
<td>(0.134)</td>
<td>(0.173)</td>
<td>(0.155)</td>
<td>(0.147)</td>
<td>(0.183)</td>
<td>(0.171)</td>
<td>(0.306)</td>
<td>(0.491)</td>
<td>(0.326)</td>
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<tr>
<td>rainy</td>
<td>0.067</td>
<td>0.072</td>
<td>0.007</td>
<td>-0.073</td>
<td>-0.061</td>
<td>-0.065</td>
<td>0.365</td>
<td>0.365</td>
<td>0.371</td>
</tr>
<tr>
<td></td>
<td>(0.177)</td>
<td>(0.190)</td>
<td>(0.182)</td>
<td>(0.203)</td>
<td>(0.224)</td>
<td>(0.213)</td>
<td>(0.358)</td>
<td>(0.367)</td>
<td>(0.362)</td>
</tr>
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<td>Hausman p-value</td>
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<td></td>
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<td></td>
<td></td>
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<tr>
<td>obs.</td>
<td>111</td>
<td>111</td>
<td>111</td>
<td>77</td>
<td>77</td>
<td>77</td>
<td>34</td>
<td>34</td>
<td>34</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.22</td>
<td>0.11</td>
<td>0.11</td>
<td>0.26</td>
<td>0.10</td>
<td>0.10</td>
<td>0.33</td>
<td>0.33</td>
<td>0.33</td>
</tr>
</tbody>
</table>
dramatically, suggesting that in these data there is considerable simultaneity going on. And in the regressions using only the data with no/small inventory change the large Hausman test p-value suggests that in these data there is no simultaneity.
Furthermore, we find, as anticipated, that when using only data for which there are no/small inventory changes, the OLS estimate of the demand elasticity is comparable to the IV estimates.
As a final check, we used the OLS estimated coefficients from the no inventory change data (column 7 of Table 3.2) to predict quantity demanded for the inventory change data. We find that the predicted demand exceeds the quantity of fish received on 27 out of 37 days in which inventory fell, and that predicted demand is smaller than the quantity of fish received on 35 out of 40 days in which inventory rose.

3.7 Conclusion

The Fulton fish market at first glance appears to be recursive because current price cannot affect the previous night’s catch. We have shown, however, that this market is actually a good example of a simultaneous market. Our explanation recognizes that the relevant supply in this market is not the previous night’s catch, but rather includes inventory changes. Because current price affects inventory changes, there is simultaneous determination of supply and demand. Textbook explanations of simultaneous equations bias should make note of this phenomenon. This explanation is not unique to the Fulton fish market. Any high-frequency market in which inventory changes are affected by price changes is subject to the simultaneity feature we have identified. To be a recursive market, a market must satisfy two criteria. First, the frequency of observation must be sufficiently short that institutional constraints prohibit feedback from current price to traditional producer supply. And second, something not spelled out in the simultaneous equations literature, price changes must not influence inventory changes that can affect the supply actually appearing on the market. Markets without substantive inventories, such as would be the case for an extremely perishable product, would satisfy this requirement.
Finally, we have also noted that whenever inventory changes are influenced by price in a high-frequency market, estimation of the supply price elasticity must be reinterpreted to encompass supply changes due to inventory adjustment. Traditional estimation overstates long-run
producer response to a price change.


First observations may lead one to the conclusion that fish markets are purely competitive markets. But the empirical analyses always reveal strong price dispersion for homogeneous or very similar goods. So the problem is to explain this price dispersion. Several authors have emphasized the 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 show here, both through a generalized least squares and a generalized moment method, that pairwise transaction prices positively depend on prices of other transactions. We bring to light a surprising paradox, in that this is a market where prices are not posted, and yet the formation of each transaction price depends on the others.¹

4.1 Introduction

For a long time, economic theory treated the market as a “pure” economic relation, ignoring the specificity of individual behaviour. The concepts of uncertainty, information differences and agent heterogeneity are absent from the Walrasian model. The Arrow Debreu general model of equilibrium incorporates the idea of incom-

¹We wish to thank Georges Bresson and Sanjeev Goyal for helpful discussions, Sandro Sapio for interesting comments. Remaining errors are ours.
plete information, but it retains the fiction of a representative rational individual with convex preferences. Much of the microeconomic literature in the second half of the twentieth century has tried to develop tools to resolve the different problems encountered in the modeling and prediction of markets, when one seeks to explain how information emerges and what level of information individuals possess. Taking into account the way in which agents interact amounts to recognizing that they are not anonymous. Their level of information depends on the specificity of the goods and/or services supplied, on the organizational structures of the transactions and on the interactions between agents. Empirical studies of specific markets have shown, in particular, that when there is asymmetry of information, social phenomena such as mimetism, cultural identity and social interactions greatly influence the results of the market.

The fish market has a long tradition in the economic literature. Many authors refer to it when they want to investigate the organization of exchanges, no matter whether they are dealing with equilibrium or disequilibrium. This market constitutes a kind of economic paradox in the sense that, in a lot of cases, at first glance, one could conclude that it is a case of a purely competitive market. The different fish markets are generally constituted by a number of sellers large enough to avoid collusion, a huge number of buyers, a collective place of transaction and exchanges carried out in a very short time-period. There are no barriers to entry in this market (traditionally, fishing boats can sell their merchandise wherever they want, they only have to pay taxes on the fish sold). But the empirical analyses always reveal strong price dispersion for homogeneous or very similar goods. The problem is therefore to explain this price dispersion. A closer look brings out some important differences with the usual representation of a Walrasian market. In particular, the fact that fish markets are held regularly (they are generally daily markets) implies non-anonymity between individuals (buyers and sellers).

We distinguish three main explanations in the economic literature. Several authors have sought to explain this discrepancy by taking into account the differences in organization. Thornton (1869), for example, observes that the equilibrium price differs depending on whether the fish is sold through English or Dutch auctions. For some other authors, like Pareto (1906) or more recently Graddy
price dispersion is mainly explained by the fact that the good is perishable and cannot be stocked. A third approach, driven by Kirman and Vignes (1990) and by Weisbuch, Kirman and Herreiner (2000) emphasizes the influence of social interactions between buyers and sellers.

Following the line of this last approach, our paper sets out to explain, through the observation and econometric analysis of the Marseille fish market, why a decentralized market where the main assumptions of pure competition are present exhibits a stable daily dispersion of prices for different units of a homogeneous good. Our main contribution to the literature consists in proposing an original way of estimating the influence of social interactions. Our hypothesis is that transaction prices strongly depend on interactions between non-anonymous individuals. In that sense, each transaction between two persons is influenced by the transactions they have made with other agents. Through a dynamic panel data analysis, we show that the dispersion of prices is persistent over time. We focus on the understanding of bilateral exchanges and bring to light the influence of others on the determination of transaction prices. Our article reveals that the price of a transaction depends on the prices of the other transactions taking place at the same moment.

The first part outlines the place of the fish market in economic literature. Sections 4.2 and 4.3 describe the functioning and particularities of the Marseille fish market. Section 4.4 presents the data, Section 4.5 the theoretical model, Section 4.6 the empirical set-up and Section 4.7 the variables and the results. The conclusion follows (Section 4.8).

4.2 The fish market in the economic literature

The fish market has regularly been used as an example by different authors to refute the simple rule that in a given market for a homogeneous good, there is a unique price, equal to the matching between supply and demand. In what follows, we show how these different authors propose various explanations, in terms of the organization of the market, the characteristics of the good, or the social interactions between the different actors.
4.2.1 The fish market features

All around the world, fish markets are organized according to one of two main mechanisms: bargaining (pairwise meeting for an exchange) or auctions, but the auction mechanisms can take different forms. At the end of the 1980s, most of the big French fish markets (Sète, Boulogne sur Mer, Lorient) operated according to a “mixed” process, with a small proportion of the fish being sold through pairwise exchanges and the biggest part of the production being sold through auctions. The auctions were the result of a political desire to make price formation more transparent (to avoid phenomena of collusion) and to speed-up the transactions (to enable the biggest possible volume of fish to be sold in the shortest possible time). The negotiated market was maintained on request by participants on both sides, which can be surprising from an economic point of view (buyers and sellers have usually conflicting interests). The buyers argued that the negotiated market allowed for a better evaluation of quality, and therefore a better product. The sellers considered that prices were higher in the negotiated market than in auctions. According to everybody concerned, the best quality is sold in pairwise transactions, while the more common species (and the biggest quantities) are sold by auction. In the 1980s, the Marseille fish market was an exception to the French rule, exchanges being conducted exclusively through pairwise contacts, after a very simple bargaining process. The diversity of the organizations might have an influence on the outcome of the markets.

Even if exchange markets have always been organized in very different ways (bargaining through pairwise decentralized transactions, English or Dutch auctions) the influence of these organizations on the formation of prices has long been ignored by the economic literature. Thornton (1869), observing two herring markets located in two towns in Great Britain, geographically very close, but one using a system of Dutch auctions and the other using English auctions, noted that these different organizations could lead to different exchange prices for homogeneous goods: “...The person who was prepared to pay the former price might very possibly be the only person present prepared to pay even so much as the latter price; and if so, he might get by English auction for eighteen shillings the fish for which at Dutch auction he would have paid twenty shillings. In the same market, with the same quantity of
fish for sale, and with customers in number and every other respect the same, the same lot of fish might fetch two very different prices” (Thornton, pp. 47-8). This observation has been strongly criticized by Mill, for whom the price or the value of an exchange emerges from the confrontation of supply and demand. In his reply, Mill considers that in some particular marginal cases (such as a market in a small fishing port) dealing with small amounts of a commodity, the law of demand may not be observed. But “where buyers are counted by thousands, or hundreds, or even scores, in any considerable markets, it is the next thing to impossible that more of the commodity should not be asked for at every reduction of price. The case of price, therefore, which the law of the equalization does not reach, is one which may be conceived, but which, in practice, is hardly ever realized” (Mill 1869).

Some years after Mill, in his “Manual of Political Economics”, Pareto (1906) reports that very often, in big cities, fish is more expensive in the morning than when the market closes. The owner of a high-class restaurant will come early in the morning and buy what he needs (in terms of quantity and quality) at a very high price. But the owner of a cheaper restaurant will come later and buy what he finds at a lower price. Marshall (1930) notes that even in a market of very short period and with perishable goods, such as a fish market, the cost of production has no perceptible influence on the day’s bargaining. In this kind of market, according to Marshall, the “haggling and bargaining” will oscillate about a mean position, which could be considered as the equilibrium price. The decisions of sellers to accept or refuse a certain price do not depend on the cost of production. The quantity of the commodity, which cannot be stored, will be used as data by the dealers, and the prices will be determined so as to clear the market. Consequently, in this situation, the formation of prices will depend on the demand on the one hand, and the quantities of goods still available on the other. It seems that, in the same year, both Pareto and Marshall showed that because fish has very particular characteristics, the prices will fluctuate in a particular way. Firstly, fish is a very perishable good: once the merchandise has been exposed in the fish market, it must be sold before the end of the day. The seller is forbidden from selling any remaining stock after this period, which would represent a pure loss for him. The second feature is that the organization of fishing is something like a “food-gathering economy”, in the sense
that fishermen have no influence on fish production and no control over weather conditions. Because the sellers have very little control over production, the only strategic variable is the price, which is strongly determined by the demand in the short term.

4.2.2 The social interactions

From the study of the Marseille fish market, Vignes (1993) has shown that one same variety of fish can be sold at very different prices on the same day. More surprisingly, the study also shows that one same buyer can buy a same variety of fish at very different prices on the same day. Kirman and Vignes (1990) show that in a context where buyers are perfectly informed about the sellers’ constraints, and can therefore estimate their reserve prices, it can be rational for some buyers to transact regularly with the same few sellers, paying a high price, but being sure of the quality of their transactions. Weisbuch, Kirman and Herreiner (2000) analyze the evolution of trading relationships in a negotiated market. The prices are not posted and the agents are imperfectly informed, as is the case in the Marseille fish market. In this situation, buyers reinforce their probability of visiting sellers as a function of the profitability of their past experience. The model shows that two far-removed types of behavior - “loyalist” and “shopper” - emerge and that the transition from one to the other is abrupt. Gallegati et al (2008) show that in the Ancona fish market, which functions through simultaneous descending auctions, the prices can vary greatly for very substitutable goods. The empirical analysis reveals that even if the influence of relationships is less obvious than in the Marseille fish market, loyalty is still present and influences the results of the auction mechanism. The hypothesis of homogeneous goods, common to most of the studies on fish markets, is rejected by Graddy (2006). This author studies a New York fish market and observes that buyers really need to see and touch the merchandise to have a clear idea of the quality. Buyers are very heterogeneous in their budget constraints and consequently in their demand, and so is the merchandise. The author considers that because of this strong differentiation, it could be more convenient to consider this market as a set of monopolistic sub-markets rather than as one whole competitive market.
4.3 The functioning of the Marseille fish market.

The Marseille fish market is a wholesale market. In 1987, it was one of the largest fish markets in the south of France, along with that in Sète (in South-West France). 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 and the buyers are essentially retailers, fishmongers or restaurant owners. Buyers can come from very far away (the Alps, Vaucluse) or from Marseille, and because this market is a long-established and daily one, everybody knows the constraints of the others.

4.3.1 The individuals

The sellers are wholesale fish-merchants who buy their merchandise from local fishing boats and from external fish-merchants: in the middle of the night, trucks arrive from Rungis or from Boulogne sur Mer with fish from the North Sea (whiting, cod, and so on). This fish was ordered two or three days before. The market takes place daily, and everybody agrees that there is regularity in the daily demand from one week to the next (a certain intensity of demand being associated with each day) and in monthly demand from one year to the next (each month having its corresponding different types of production and different demands). These regularities help the merchants in determining their orders. At the same time, fishing boats arrive from the nearby Mediterranean and unload local species of fish, such as bass or sole. The fishing-boat owners deliver their catch to the merchants with whom they are associated. They will get a percentage on the sale. Hence, if the merchant does not sell the merchandise, the fisherman will earn very little money (the reservation price, fixed by the European Community). Clearly, if a merchant is not efficient enough (not selling the catch, or selling at too low a price) the fisherman will change partners. Once they have placed their orders, the sellers have no more 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 loyalty contracts which exist.
between certain particular sellers and buyers. Furthermore, one of the particularities of this market is that prices are not quoted; everybody watches everybody else (particularly sellers) to estimate the level of prices fixed by the others. In the same sense, each buyer, or more exactly each visit, can be a source of information for the market: if Mr. A goes to visit Mr. B, it means that he has not bought from Mr. C (which he usually does) and this is almost certainly because Mr. C was too expensive today... Buyers are essentially retailers, which involves very particular constraints on the demand side. They can be mainly restaurant owners, official buyers for institutions (hospitals, company canteens, schools), supermarket buyers or fishmongers. A buyer who arrives at the market early in the morning decides how much to purchase by maximizing his expected gain. With each failed transaction, he associates an expected loss (if he has nothing to sell, he cannot make a profit), rather than a null surplus. This particularity entails a positive risk aversion for the buyers, which is different from other exchange markets (for more details see Kormendi 1979).

4.3.2 The good

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 four a.m.) must be sold before the market closes (around eight a.m.). A lot of different varieties of fish are sold, but the data are encoded following a well-defined European scale. At first glance, the analyst could therefore assume homogeneity within each variety, and ignore explanations in terms of vertical or horizontal differentiation.

4.3.3 The market place and the transaction process

One Tuesday, at 3 o’clock, in the “Saumaty halle à marée” (the wholesale fresh fish market in Marseille), 44 sellers stand in front of around 125 buyers. On average, 2372 kilos are sold every day. The market is always held in the same place. The purchase is a negotiated one, and is done in a very short time. The prices are not posted. The bargaining process is something like a “take it or leave it”. Because time is very short, individuals do not spend much time bargaining. The buyer indicates the weight and the type
of fish he is interested in, the seller gives a price, the seller accepts or refuses. Sometimes, the seller can accept but for a lower weight. This is due to the positive risk aversion of the buyers. Here, we must remember that if a buyer cannot buy a certain species of fish, he will not be able to satisfy his expected demand (as a retailer) and he runs the risk of losing his reputation or his customers.

At four o’clock in the morning the market opens, and the first transactions are made between some sellers and the buyers who are most in a hurry (generally the ones who come from far away and have to leave early) or the most anxious (the owners of expensive restaurants who really need to find good quality of specific species). Most of the sellers are aware of these characteristics and the buyer is likely to have to pay a high price (the monopoly price). Even if a buyer wants to search for a lower price, it is most unlikely that he will succeed, because everybody knows he has to leave early. The best solution for him is to establish a kind of implicit contract of loyalty with one or two sellers, to ensure him a constant level of quality and an average price. The same day, before eight o’clock in the morning, the last transactions are made between the sellers and the last buyers. These last buyers have no specific time or quality constraints (they work in the neighborhood or run shops in working-class areas). The exchanges are made at very high prices or very low prices, depending on whether there is excess demand or excess supply.

4.4 The data

Our database describes the daily transactions in the market of Marseille. For each transaction, we know the date of transaction, the identities of the buyer and seller involved in the exchange, the species of fish, the quantity and the price. Our sample covers transactions from January 1988 to December 1990, representing more than 132,000 transactions. Although 15 different species of fish are registered on this market, three of them (whiting, cod and sole) actually represent 75% of the transactions. On average, 44 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. Over this period, between 2 and 7 tons of fish were sold annually (2 tons the first year, 5 tons the second and 7 tons
the last year). This difference is due partly to variations in the catch and partly to a difference in the recording of data (1988 was the beginning of data recording and some of the sellers did not participate in the operation). Our analysis mainly focuses on the explanation of daily price transactions, taking into account the effect of interactions between individuals.

Figure 4.1 suggests that the situation on this market is quite heterogeneous, ranging between the sellers who have a huge number of buyers and the seller who has just one buyer (this couple meets 13 times). The mean is at 100 and the max at 266. A small number of sellers appear to have something like a contract relation with some buyers: we can quote here the case of a seller who essentially sells sardines to the same buyer, an important retailer, to whom he sells a large volumes but through very few transactions. Some others, like the one who sold to 266 different buyers during the period studied, seem to be specialized in selling to a large number of buyers.

Figure 4.2 represents the prices and volumes of different transactions for a same species of fish (sole, coded 44) made by a certain buyer on a certain day of the year. This figure suggests that there is no exact negative relation between the weight sold through a transaction and the price of this transaction. Clearly, on this market, the transaction price does not decrease with the weight through the day.

4.5 The theoretical model

It appears now that two main characteristics of the studied market are that there is a huge dispersion of prices for homogeneous goods sold at the same time and that people know each other’s intrinsic characteristics. On a market where agents can be considered as rational (buyers are resellers and not consumers with some chaotic preferences) and where anonymity does not exist, we first make the hypothesis that interactions influence the outcome of exchanges. Our hypothesis is in the line of Manski (2000), who assumes that markets emerge from constraint interactions. The decisions of agents to purchase certain amounts of a good collectively determine prices, which in turn determine the quantities exchanged. But economists long considered markets as institutions where agents in-
Figure 4.1: There is no exact correspondence between the number of buyers met and the quantities sold
Figure 4.2: There is no pure decreasing relation between the prices and the quantities sold
teract through an anonymous process of price formation. To break with this assumption of anonymity, Brock and Durlauf (2001) distinguish between local and global interactions: the interactions in the neighborhood of an agent influence his decisions, while the others do not. Kranton and Minehart (2001) also break with the assumption of anonymity, developing a model of exchange as a network between buyers and sellers: in this framework, a buyer and a seller must have a relationship (or a link) to trade. A buyer can obtain a good from a seller if and only if there exists a link between them. Gale and Kariv (2006) consider a financial market as an incomplete network (one were some pairs of traders cannot trade with each other). The main reasons for incompleteness are asymmetry of information and transaction costs, which imply some particular relationships between subgroups of agents.

We then adopt the hypothesis that each price and quantity exchanged on a given day between two individuals (a buyer and a seller) results from the intersection of a partial demand and a partial supply. This partial demand and offer depend respectively on the other quantities and prices exchanged during the same day, by the seller in question with other buyers and by the buyer in question with other sellers. We finally assume that daily exchanges are simultaneous ones.

The following hypotheses describe the market under study:

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. Transactions occur over the time span of a day.

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 to 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 have paid to the other sellers, and the sum of quantities the buyer purchases from other sellers.

We can now write down the following model:
At each time \( t = 1, 2, ..., T \) a seller \( i \) with a supply \( q_{i,j}^O \), \( i = 1, 2, ..., N \) meets a buyer \( j \) with a demand \( q_{i,j}^D \), \( j = 1, 2, ..., M \).

\[
q_{i,j}^D = f(p_{i,j}, \bar{p}_{k\neq i,j}, \sum_{k\neq i,j} q_{k,j}) \tag{4.1}
\]

\[
q_{i,j}^O = f(p_{i,j}, \bar{p}_{i,k\neq j}, \sum_{k\neq j} q_{k,j}) \tag{4.2}
\]

Deriving simultaneously the equations 4.1 and 4.2 allows us to express a transaction price in terms of other prices and quantities.

\[
p_{i,j} = g(\bar{p}_{k\neq i,j}, \bar{p}_{i,k\neq j}, \sum_{k\neq j} q_{i,k} \sum_{k\neq i} q_{j,k}) \tag{4.3}
\]

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

### 4.6 The empirical set-up

We perform our econometric analysis in two steps. We first evaluate the influence of different variables in the static case, then check the persistency of phenomena in a dynamic estimation. Both in the static and the dynamic estimations we will distinguish between direct effects and indirect effects of the prices of other transactions on the price of one transaction.

#### 4.6.1 The basic empirical model

From the theoretical model presented in section 4.5, we propose to estimate the following system:

\[
p_{i,t} = \bar{p}_{k\neq i,t}^i \beta_1 + \bar{p}_{i,t}^{k\neq j} \beta_2 + \bar{p}_{k\neq i,t}^{k\neq j} \beta_3 + \alpha_1 \sum_{k\neq i} q_{k,t}^i + \alpha_2 \sum_{k\neq j} q_{i,t}^k + Y_t + M_t + D_t + r_{i,t} + r_{j,t} + v_{i,t} \tag{4.4}
\]

\( i = 1, 2, ..., N; \quad j = 1, 2, ..., M; \quad t = 1, 2, ..., T \)
\[ v_{it} = \mu_i + \delta_{it}, \quad \mu_i \sim i.i.d.(0, \sigma_{\mu_i}^2), \quad \delta_{it} \sim i.i.d.(0, \sigma_{\delta}^2) \] (4.5)

This market is a daily one, 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 fishing activity varied, following variations in European quotas, which also had a great impact on the functioning of markets. We then introduce dummy variables in the estimated Equation 4.4 which will allow us to isolate the influence of the different time scales \((D_t \text{ for days, } M_t \text{ for months, } Y_t \text{ for years})\) and concentrate on the determinant of prices at a given time.

In Equation 4.4, the explained variable is \(p_{i,t}^j\), which designates the transaction price. The model estimated is a log-log one, which allows to directly interpret the estimated coefficients as elasticities. The explanatory variables are related to the influence of the time (5 dummies for the days of the week, 11 month dummies and 2 year dummies), the influence of the decisions of other individuals in terms of prices and quantities, the influence of the “types” of sellers and buyers (shoppers or loyalists, evaluated by the number of sellers per buyer and the number of buyers per seller). \(v_{it}\) is the error term, which is broken down into two parts (see Equation 4.5): \(\mu_i\), which corresponds to an unobserved transaction-specific time-invariant effect (it takes into account the heterogeneity of the transactions among sellers) and \(\delta_{it}\), which is an error term. \(\beta_1, \beta_2, \alpha_1, \alpha_2\) are the parameters to be estimated through a generalized least square estimation. A full description of all variables is provided in Section 4.7.1. The estimation results are presented in Tables 4.1 and 4.2 below. In order to isolate the main determinants of the formation of transaction prices, we associate specific distributions of prices and quantities bought or sold during a day with each buyer and seller. To simplify the estimation, we explain the prices of one specific variety of fish. Clearly, it would be easy to widen our analysis, by taking into account the main species sold on this market and evaluating the substitution effects between them.
4.6.2 A dynamic panel data model

We now propose to estimate a dynamic panel model to better explain the formation of transaction prices on a daily market, with non-anonymous individuals. The fact that individuals know each other could suggest that learning and memory play an important role in this market. A possible hypothesis would be that the endogenous explained variable (the price of the transactions) in our model can clearly depend on the lagged variable. In other words, we can imagine that repetitive transactions between individuals can be influenced by the past history. 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 on the history of transactions. In this case, the lagged variable would have no influence on the current one, in a frame of rational naïve anticipations (cf. Ezekiel 1938, quoted by Bresson and Pirotte 1995).

One way of evaluating the influence of the past (already often used in the literature on this topic) would be to consider an autoregressive model measuring the evolution of prices through the different days of the market. We believe that this approach fails to explain the exact dynamic of specific pairwise transaction prices. 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.

To better capture the intrinsic dynamics of pairwise transactions, we now propose to estimate the following model:

\[
p_{i,t}^j = p_{i,t-1}^j + \bar{p}_{k \neq i,t}^j \beta_1 + \bar{p}_{i \neq k,t}^j \beta_2 + \bar{p}_{k \neq j,t}^j \beta_3 + \alpha_1 \sum_{k \neq i} q_{k,t}^j + \alpha_2 \sum_{k \neq j} q_{k,t}^j + Y_t + M_t + D_t + r_{i,t} + r_{j,t} + v_{i,t}
\]

(4.6)

\[
v_{i,t} = \mu_i + \delta_{i,t}, \quad \mu_i \sim i.i.d.(0, \sigma_\mu^2), \quad \delta_{i,t} \sim i.i.d.(0, \sigma_\delta^2)
\]

(4.7)

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 et al. (2000) and Schrooten et al. (2005), we use a generalized method of moments (GMM) estimator applied to dynamic models using panel data. 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.

In line with the authors quoted above, we use the alternative “system GMM estimator” proposed by Arellano (1995) and Blundell and Bond (1998), which allows to reduce the potential biases and imprecision associated with the usual difference estimator by combining the regression in differences and the regression in levels in the same system. As Windmeijer (2005) notes, the estimated asymptotic standard errors of the efficient two-step GMM estimator will be severely downward-biased in small samples, and thus we correct the standard errors for this bias using the method proposed by the same author.

The ratios (of buyers per seller and sellers per buyer) are the only explanatory variables that we treat as strictly exogenous variables. We therefore include them as instruments in our estimation. Finally, the two-period lag of the transaction price is used as an instrument only in the level equation.

4.7 The variables and the results

4.7.1 The variables of the model

Here, we estimate the influence of both direct and indirect effects on the price of a transaction. Our hypothesis is that a transaction between a buyer and a seller is directly affected by the prices the seller has negotiated with other buyers and the prices the buyer has negotiated with other sellers. The transaction might also be affected by indirect interactions, mainly by the transactions carried out by buyers the seller does not meet (and the sellers the buyer does not meet). To test this hypothesis, we set out to estimate the influence of the other transaction prices and other quantities
exchanged on the result of one particular transaction. For this purpose, we associate with each transaction price, the average price that the seller in the transaction asks from his other buyers on the same day, the average price that the buyer pays to his other sellers on the same day, and the sum of quantities that each participant in the transaction has sold to or bought from other buyers or sellers during the same day. Descriptive results presented in section 4.4 suggest that if some buyers meet a lot of different sellers, others always exchange with the same few sellers. Likewise, some sellers are in contact with a lot of different buyers, while others meet very few buyers. To evaluate the importance of these different behaviors, we compute a daily ratio for each buyer and seller $r_{i,t}$ and $r_{j,t}$, representing the number of sellers (or buyers) met.

We evaluate the influence both of prices paid by other buyers to the seller and of prices paid by the buyer to other sellers. We call this a direct effect, as these prices result from direct links (between the seller and the other buyers or between the buyer and the other sellers). To do so, with each transaction between a certain seller $i$ and a certain buyer $j$, we associate two average prices: one ($p^{k\neq j}_{i,t}$) is the average of all the prices paid to a certain seller $i$ by the other buyers he transacts with during one same day (except of course, the price paid by the buyer $j$). The other ($p^{k\neq i}_{j,t}$) is the average price a certain buyer $j$ pays to the other sellers he transacts with on the same day. We then estimate the indirect effect ($\bar{p}^{k\neq i}_{j,t}$), calculating the average price the buyers who have not met $i$ have paid to the other sellers.

We also need to evaluate the influence of quantities bought from other sellers and of quantities sold to other buyers. We then compute for each buyer $\sum_{k\neq j} q^b_{k,t}$, the sum of quantities he buys during a given day, and for each seller, the sum of quantities he sells during the same day $\sum_{k\neq i} q^s_{k\neq i,t}$ to other buyers.

4.7.2 The empirical results

In Table 4.1 and 4.2, we present the main results of the random effect and dynamic models. The three first models are variations of the static model and were computed through an incremental process. We first estimate the influence of the indirect effect on the price of a pairwise transaction. This effect is positively signifi-
cant at 10%, which suggests that the prices of other agents (other buyers and other sellers) influence the price decided between two individuals. In other words, a high level of prices on the market increases the transaction price. In a second estimation (model 2), we evaluate the influence of the ratios on the price transaction. These two variables have a significant effect at 10%; one positively, the other negatively. A seller who meets a high number of buyers will charge high prices, while a buyer who meets a great number of sellers will pay lower prices. But these two effects disappear in the third model, when we introduce the direct effects (the average price quoted by the seller to the other buyers and the average price paid by the buyer to the other sellers). These prices are significant at 1%, which suggests a strong impact, and they are both positive. Clearly, this impact absorbs the influence of the other variables (prices of the other transactions and ratios). It seems that when a buyer buys at high prices from other sellers, he continues to buy at high prices: we find again here the results found in a previous paper, where we 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 specialization of sellers has a stronger influence than that of buyers. One explanation could be that sellers have a strong reputation on the market (as “high price seller” or “low price seller”) and changing strategy would be very costly, while some buyers can sometimes adopt a kind of mixed strategy, visiting a lot of sellers on one day and very few on another.

In this model, the quantities sold by the seller also have a 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 has no influence on the price of a certain transaction, even if the coefficient is weakly negative. One explanation could be that even if 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 enough to influence the estimation.

Without any surprise, we observe the influence of different seasonal variations (yearly, monthly, daily). Prices are lower in April and November. They were lower in 1988 and 1989 than in 1990. The prices also vary through the week.
Table 4.1: Generalized Least Squares and Generalized Moment method estimations results: part 1
dependent variable: transactions prices (in logarithm)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_{j,t-1}^j$</td>
<td>——</td>
<td>——</td>
<td>——</td>
<td>-.1669</td>
</tr>
<tr>
<td>$p_{k\neq j}^j$</td>
<td>——</td>
<td>——</td>
<td>.0272</td>
<td>-.0038</td>
</tr>
<tr>
<td>$p_{k\neq l,t}^j$</td>
<td>——</td>
<td>——</td>
<td>.6513***</td>
<td>.4942***</td>
</tr>
<tr>
<td>$q_{k\neq j}^j$</td>
<td>——</td>
<td>——</td>
<td>.3377***</td>
<td>.2281*</td>
</tr>
<tr>
<td>$q_{k\neq l,t}^j$</td>
<td>——</td>
<td>——</td>
<td>-.0717***</td>
<td>-.0549**</td>
</tr>
<tr>
<td>Weekly dummies</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monday</td>
<td>-1.000**</td>
<td>-9.431**</td>
<td>-.2186</td>
<td>-.1458</td>
</tr>
<tr>
<td>Tuesday</td>
<td>-.0954**</td>
<td>-.1011***</td>
<td>-.0678**</td>
<td>-.0699*</td>
</tr>
<tr>
<td>Wednesday</td>
<td>-.0503</td>
<td>-.0543</td>
<td>-.0272</td>
<td>.0224</td>
</tr>
<tr>
<td>Thursday</td>
<td>-.0955**</td>
<td>-.1034**</td>
<td>-.0870**</td>
<td>-.0770**</td>
</tr>
<tr>
<td>Friday</td>
<td>-.0854**</td>
<td>-.0917**</td>
<td>-.0713**</td>
<td>-.0586**</td>
</tr>
<tr>
<td>Saturday</td>
<td>Ref.</td>
<td>Ref.</td>
<td>Ref.</td>
<td>Ref.</td>
</tr>
</tbody>
</table>
Table 4.2: Generalized Least Squares and Generalized Moment method estimations results: part 2

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Monthly dummies</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>January</td>
<td>.0022</td>
<td>-.0021</td>
<td>.0049</td>
<td>-.0652</td>
</tr>
<tr>
<td>February</td>
<td>-.0030</td>
<td>-.0007</td>
<td>.0079</td>
<td>-.0516</td>
</tr>
<tr>
<td>March</td>
<td>.0059</td>
<td>.0037</td>
<td>-.0107</td>
<td>-.0438</td>
</tr>
<tr>
<td>April</td>
<td>-.1158**</td>
<td>-.1238**</td>
<td>.0818*</td>
<td>-.0398**</td>
</tr>
<tr>
<td>May</td>
<td>-.0486</td>
<td>-.0529</td>
<td>-.0486</td>
<td>-.0841</td>
</tr>
<tr>
<td>June</td>
<td>-.0855</td>
<td>-.0838</td>
<td>-.0320</td>
<td>-.0719</td>
</tr>
<tr>
<td>July</td>
<td>.0172</td>
<td>.0149</td>
<td>-.0123</td>
<td>-.0496</td>
</tr>
<tr>
<td>August</td>
<td>-.0184</td>
<td>-.0239</td>
<td>-.0341</td>
<td>-.1342</td>
</tr>
<tr>
<td>September</td>
<td>-.056</td>
<td>-.0794</td>
<td>-.0681</td>
<td>-.2009*</td>
</tr>
<tr>
<td>October</td>
<td>-.1023*</td>
<td>-.1081*</td>
<td>-.0646</td>
<td>-.0575</td>
</tr>
<tr>
<td>November</td>
<td>-.1649***</td>
<td>-.1658***</td>
<td>-.0970*</td>
<td>-.2340*</td>
</tr>
<tr>
<td><strong>Yearly dummies</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year 1988</td>
<td>.1008***</td>
<td>.1048***</td>
<td>.0741***</td>
<td>.1039*</td>
</tr>
<tr>
<td>Year 1989</td>
<td>-.1365***</td>
<td>-.1354***</td>
<td>-.1334***</td>
<td>-.1201*</td>
</tr>
<tr>
<td>Constant</td>
<td>3.0767***</td>
<td>5.0974***</td>
<td>4.0999***</td>
<td></td>
</tr>
</tbody>
</table>

Sargan test \( \chi^2(440) = 292.15 \)
\( Pr > \chi^2 = 0.0000 \)

Arellano Bond test AR (1)
\( z = -6.59 \)
\( Pr > z = 0.0000 \)

Arellano Bond test AR (2)
\( z = -1.12 \)
\( Pr > z = 0.2615 \)

Notes: * significant at 5%; ** significant at 10%; *** significant at 1%.
The estimated static model reveals that there are strong interactions between all the prices on this market, and that buyers who pay high prices continue to pay high prices, whatever the transaction considered; it also reveals that, for a given day, sellers post prices which are either high or low. An important question now is to determine whether these kinds of pure strategies (high prices or low prices) are continuous over the time (which would define real “price determination profile”) or are stochastic, which would suggest that high-price individuals one day might become low-price individuals on another day. For this purpose, we estimate a dynamic model.

The dynamic estimation produces two important results. One is that the lagged variable has no influence on the transaction price. In other words, the price of one exchange does not depend on the prices of past exchanges. We believe that on this market, people know each other too well to be involved in learning procedures. The other result is that the results obtained through the estimation of the static model are reinforced. The different time scales (days of the week, months and years) still appear to greatly influence the prices, which also depend positively on the prices of other transactions and negatively on the quantities sold by the seller.

We observe that the effect of the variable “average price charged by the seller to the other buyers” is still significant at 1%, while the effect of the variable “average price paid by the seller to the other buyers” is less significant (5%) than in the static model. The indirect effects and the ratios effect, significant when they are estimated alone, are absorbed by the direct effects (they are significant when they are the only regressors). On this market, the network of links changes every day (according to the number of buyers present and the intensity of the exchanges) and these changes mostly affect the determination of prices.

4.8 Conclusion

This article seeks to explain the determinant of transactions between pairs of individuals. A static estimation clearly shows the influence of interactions between different transaction prices on this daily non-anonymous market. Transaction prices are influenced both by direct and indirect effects, but the indirect effects
are absorbed by the direct ones. In other words, every time a buyer accepts a price from a seller, he gives him information concerning the market environment. When people know each other, and know their own characteristics and constraints, transaction prices depend not only on the state of the market (supply and demand) but also on the characteristics of the agents involved and of the others they meet. On the seller side, it appears that sellers selling large quantities reduce their prices, which is in line with a very classical result of microeconomic theory. The dynamic estimation does not reveal a learning effect. This could suggest that on this market, at least for fish sold regularly, anticipations are naïve and that over a long time period, buyers continuously pay the same level of prices. This is in line with previous results on this market. It could also suggest that when agents are non-anonymous, the outcomes of the market (in terms of prices and quantities exchanged) depend on the set of local social interactions. We have brought to light a surprising paradox, in that this is a market where prices are not posted, and yet the formation of each transaction price depends on the others.
Table 4.3: Descriptive statistics on the main variables used in the estimated models

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>prices</td>
<td>20387</td>
<td>175.6814</td>
<td>157.2281</td>
<td>.4712389</td>
<td>3750</td>
</tr>
<tr>
<td>( p_{j}^{k \neq i, t} )</td>
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<td>175.6814</td>
<td>75.4488</td>
<td>5.333333</td>
<td>1187.5</td>
</tr>
<tr>
<td>( p_{i, t} )</td>
<td>20387</td>
<td>175.6814</td>
<td>141.1737</td>
<td>.4712389</td>
<td>2750</td>
</tr>
<tr>
<td>weights</td>
<td>20387</td>
<td>78.95689</td>
<td>157.6759</td>
<td>2</td>
<td>5325</td>
</tr>
<tr>
<td>( q_{k \neq j}^{i, t} )</td>
<td>20387</td>
<td>148.3359</td>
<td>193.5013</td>
<td>4</td>
<td>5325</td>
</tr>
<tr>
<td>( q_{j}^{k \neq i, t} )</td>
<td>20387</td>
<td>2364.669</td>
<td>1820.337</td>
<td>5.333333</td>
<td>15086.36</td>
</tr>
<tr>
<td>( r_{i, t} )</td>
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<td>4.418296</td>
<td>1.660619</td>
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<td>6.77101</td>
</tr>
<tr>
<td>( r_{j, t} )</td>
<td>20387</td>
<td>.3108046</td>
<td>.1959313</td>
<td>.0340252</td>
<td>.7825791</td>
</tr>
</tbody>
</table>

Appendix

Descriptive statistics

The table 4.3 presents some descriptive statistics on the main variables describing the data set used in this article.
The figures 4.3 and 4.4 represent the evolution of the daily and monthly marginal effects.
Figure 4.3: Daily marginal effects
Figure 4.4: Monthly marginal effects


In this paper we analyze the fish market of Ancona (MERITAN) where transactions take place by means of three simultaneous Dutch auctions. The main question is how much the presence of a Dutch auction affects buyers’ behavior. Evidence from the data shows that buyer-seller relationships are less evident than in a pairwise bargaining market such as the Marseille Fish market but a significative amount of loyalty is still present under the auction mechanism. The paper explains also the “declining price paradox” for the fish market of Ancona linking the price stopping rule followed by the buyers to the relationship between last transactions variation in price and the quantity of fish of the day. The average price tends to increase for last transactions in days characterized by limited (compared to customers’ demand) supply of fish.\footnote{We gratefully acknowledge the participants of the workshop “The Emergence and Impact of Market Institutions: The Market for Fish and other Perishable Commodities”, Tromsø (Norway), 5-6 July 2007 for their helpful comments.}

5.1 Introduction

Fish markets have long been a source of fascination for historians and for economists. To the former we owe detailed
descriptions of how fish markets operated in different places at different times. To the latter we owe various accounts of how prices are formed on these markets and models of behavior of the buyers and sellers. We have extensive accounts of the functioning of fish markets starting with those in early Greece. A detailed account of the functioning of the surprisingly sophisticated main fish market in Rome is given by De Ruyt (1983). The first market bubble is probably that for red mullet, a Mediterranean fish which became highly prized at the time of the Romans. Cicero, Horace, Juvenal, Martial, Pliny, Seneca and Suetonius all discuss in detail the price of this fish which they considered to be unreasonable and based on a fad. The price of large specimens of the fish rose to extraordinary levels during the Roman empire and at one point three specimens fetched 30,000 sesterces. Even allowing for the problems of converting to modern prices (the conversion gives 300$), this was out of proportion to other consumption goods. As a result the emperor Tiberius was moved to impose a sumptuary tax on the fish market. The bubble burst and Macrobius noted later that prices had become “reasonable” again. The fish market was an important feature of Mediterranean life and since this was one of the first areas in which markets developed it is not surprising that there are many accounts of their functioning from the time of the Greeks till the present.

This paper will analyze data from the Ancona fish market, which probably exists since the early Roman period. We have detailed data for the transactions made on this market which is organized as three simultaneous Dutch (descending price) auctions. This provides us with an opportunity to compare the data from this market with those from other fish markets and to see if similar stylized facts emerge. Secondly, we also have the possibility to see if our data exhibits the features found in auction data or predicted by auction theory. Before doing this however, we have to answer a question: why choose a fish market? The answer is relatively simple: the particular interest of fish markets for economists is that they exhibit two features which make them a natural subject of economic analysis. Firstly, fish is a perishable good and the fact that, as a result, stocks cannot be carried over makes the
formal analysis of the market simpler. Secondly, the organization of such markets varies from location to location with little obvious reason. In Iceland, for example, there are 32 auctions, 18 of these are English, i.e. rising price, and 14 are Dutch, i.e. descending price. At Lorient in France, fish is sold through a combination of pairwise trading and auction, whilst at Sète it is sold by Dutch auction and at nearby Marseille by pairwise trading. The fish market in Sydney is conducted as two simultaneous Dutch auctions, whilst that at Ancona has three such auctions. The comparison of the outcomes under different forms of organization is an obvious research topic but one which has not received much attention to date. This paper will make a modest contribution in that direction by relating the facts from the Ancona market to those from earlier studies of fish markets.

5.2 The literature

Fish markets have a long tradition in the economic literature. The first serious theoretical debate on the subject was that between John Stuart Mill (1869) and Thornton (1870). The question at issue was the nature of the prices charged for the same type of fish during auctions. The two points of view were firstly that there were either several possible equilibria or no equilibrium prices at all whilst the opposing point of view proposed that what was observed were out of equilibrium or disequilibrium prices. This debate was reopened by Negishi (1986) and was followed by a discussion by Ekelund and Thommesen (1989) and a reply by Negishi (1989). What emerged as the central issue of this debate and one which will be relevant for this paper is how we interpret the notion of an equilibrium price on a market such as that of fish.

Since, as we have said, fish is essentially perishable, markets such as Ancona, can be considered as ones in which in each period stocks are fixed and the buyers’ strategic variable are their bids. This of course depends on the sort of market organization which is being considered. In markets such as Marseille the prices proposed by the sellers and the counter offers made by the buyers are the strategies but in markets such as
Ancona, Sydney or Sete the aggregate stocks available on a day are indeed fixed the prices can hardly be considered as strategic variables since they are set through the auctioneer. In Section 5.4 we propose to examine a number of features using the available data (see Section 5.3 for a dataset description). We can basically divide the analysis of this section into two points, the price behavior and the buyers’ and sellers’ characteristics and their relationship with each other.

In subsections 5.4.1 and 5.4.2 we will test for the “declining price paradox” found by a number of authors in auctions with multiple lots such as Ashenfelter (1989) and McAfee and Vincent (1993). This feature has been attributed to fish prices by Marshall and Pareto but does not seem to be present in the data from Marseille (see Hardle and Kirman 1995).

In subsection 5.4.3 we will test for another feature of fish markets found by Weisbuch et al. (2000), the loyalty of buyers to particular sellers. In their situation buyers and sellers meet face to face and some buyers become extremely loyal to certain sellers. In our context the equivalent stylized fact would correspond to certain buyers always buying their fish from the same vessel. What data show is that even if the catches of each vessel are put on a belt sequentially in random order, loyalty is present and the buyers are in a certain sense intelligent. In Section 5.4.4 we verify agents’ price performances. Section 5.5 concludes.

5.3 Description of MERITAN

The MER.I.T.AN (“MERcato ITtico ANcona” Italian for Fish market of Ancona) is open 4 days a week (Tu.-Fr.; 3.30-7.30). It consists of 3 simultaneous Dutch auctions with about 15 transactions in total per minute. The total value of the fish sold amounts to 25millions per year.

Each type of fish is arranged in cases of about 5-7 Kilograms. Each morning the vessels are randomly assigned to one of the three conveyor belts and begin putting the cases on it. When the selected seller puts a case on the belt the price display is

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2The prediction of traditional auction theory can be found in McAfee and McMillan (1987).
set (the auctioneer decides the price) and starts going down while the case moves toward the end of the belt. Buyers watch the three displays and can bid on one or more of them, the first person to push the button at the price that has been reached wins the auction.

There are about 170 buyers. 20 of them are wholesalers while 150 retailers (pedlars, outdoor market sellers, fish shops); in any case they are not the final consumers. There are 70 sellers. The data we use in the paper are relative to one of the three conveyor belts. They cover the period from the 19th September 2002 to the 28th of May 2003. The database represents 53555 transaction for a total weight of 360115 kg. During this period 70 sellers and 149 buyers exchanged of 110 transaction classes on this specific conveyor belt (data for the whole market are more comprehensive). Note that what we call a transaction class is different from a species (see the second column of the table below for examples of transaction classes).

The data are collected daily using an electronic device. For each case traded the data reports

- The day, month and time (hour and minute) of the transaction.
- The weight.
- The price per kilo and total.
- The identification number of the seller (vessel).
- The identification number of the buyer.
- The transaction class (T.C. hereafter) and its identification number.

The following table reports the number of transactions and the total weight for the main TCs, buyers and sellers.
The column Transac. reports the number of transactions in the whole period; while Kg. is the total weight of the fish exchanged.

To complete the description of the market we examine buyers and sellers size distributions. We define the size as the weight of the fish bought or sold by the agents. As shown in Figure 5.1, there is no dominant size among the sellers while the buyers are clustered on the small size. The distribution of buyers presents a notable peak while that of sellers is rather flat. On the other hand it is evident that there are a few very large buyers. (The graphs are obtained non parametrically using kernel smoothing techniques with a Gaussian kernel, where $h$ is the bandwidth).

### 5.4 Empirical evidence

In this subsection we take a closer look at two questions. First, we analyze the way in which prices are formed and the dynamics of this process. Second we investigate the effect of the auction mechanism. In this second context, the two main questions are: i) does the auction destroy buyer-seller relationships? ii) Despite the auction mechanisms are there buyers (sellers) obtaining lower (higher) prices than others?

![TRANSACTION CLASSES Table]

<table>
<thead>
<tr>
<th>ID</th>
<th>Name</th>
<th>Transac.</th>
<th>kg.</th>
<th>ID</th>
<th>Transac.</th>
<th>kg.</th>
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<td>52</td>
<td>1848</td>
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<tr>
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<td>23271.69</td>
<td>78</td>
<td>3281</td>
<td>25350.2</td>
<td>143</td>
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<td>1</td>
<td>2676</td>
<td>19177.11</td>
<td>44</td>
<td>1652</td>
<td>10764.82</td>
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<td>80</td>
<td>2584</td>
<td>19090.16</td>
<td>148</td>
<td>1651</td>
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<td>Mixed second choice</td>
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<td>11377.67</td>
<td>279</td>
<td>2027</td>
<td>14143.79</td>
<td>134</td>
<td>1623</td>
<td>10780.86</td>
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<tr>
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<td>14236.97</td>
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<td>13294.6</td>
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</tr>
<tr>
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<tr>
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<td>8599.14</td>
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<tr>
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<td>Big sea-ben</td>
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<td>1179</td>
<td>9857.41</td>
<td>38</td>
<td>1361</td>
<td>10719.88</td>
</tr>
</tbody>
</table>

The column Transac. reports the number of transactions in the whole period; while Kg. is the total weight of the fish exchanged.
5.4.1 Price-quantity relationship

First of all we want to check the existence of a negative relationship between price and quantity. To make this kind of test it is not sufficient to plot the data of each transaction. Remember that the fish are arranged in cases with more or less equal weights, this means that a plot of quantity (weight) and price for each transaction would yield an inelastic relationship (a vertical line on the price-quantity plane) just because the quantity cannot change freely. To avoid this problem we use the average daily price, \( P_m \), and the daily quantity, \( q_t \) (these quantities relate to all the TCs).

To analyze the aggregate price-quantity relationship it is better to differentiate the series since the daily average price \( P_m \) (and also daily quantity \( q_t \), even though less evident; see the unit root tests below) is a non-stationary process (obviously because fish price rises over time; see Figure 5.2, left panel). The value of the augmented Dickey-Fuller test (ADF; 4 lags are used to compute the unit root test) for daily average price \( P_m \) is equal to -1.37. Critical values in ADF test are -2.888 (5%), -3.491 (1%) so the unit root hypothesis for \( P_m \) is not rejected. But is rejected for the differenced series \( DP_m \) (ADF test = -6.784; Critical values: -2.888 (5%), -3.492 (1%)).

Regarding the \( q_t \) series, the ADF test is -2.953. Critical values
are -2.888 (5%), -3.491 (1%). The unit root hypothesis is rejected at 5% level but not rejected at 1%. For the differenced series $Dqt$ the unit root hypothesis is rejected at both levels ($ADF = -8.76$; critical values are -2.888 (5%), -3.492 (1%)).

Figure 5.2 (right panel) shows the scatter plot of the differenced daily average price ($DPm$) and the differenced daily quantity ($Dqt$; units are 1000 Kg). Table 5.1 reports regression parameters. The aggregate slope is negative (-0.256) and statistically significant.

<table>
<thead>
<tr>
<th></th>
<th>Coeff.</th>
<th>Std.Error</th>
<th>t-value</th>
<th>t-prob</th>
</tr>
</thead>
<tbody>
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<td>0.075</td>
<td>0.284</td>
<td>0.777</td>
</tr>
<tr>
<td>Dqt</td>
<td>-0.256</td>
<td>0.064</td>
<td>-3.990</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Table 5.1: Regression of $DPm$ versus $Dqt$.

To verify that the result is not affected by weekly stagionality we compute also the regression using day-of-the-week differences. In other terms, every day of the week is differenced with respect to the correspondent day of the previous week. The regression gives a slope of -3.68 with a t-statistics of -5.39 that, in absolute value, is above the significance level of 1%. This aggregate behavior does not always have a counterpart in the microeconomic data. Indeed plotting the date for a single buyer often yields a rather different picture: price doesn’t matter at low quantity levels. We show this phenomenon in Figure 5.3 (left panel) where we select the days on which one of the largest buyers bought less than 200 Kg. of fish. In other cases examining the data for medium size buyers one can observe a reduction of the price volatility for increasing quantities, but the price has no trend as seen in the right panel of the same figure. So any aggregate characteristic is not the reflection of individual behavior.

Our analysis explains the downward sloping price quantity aggregate relationship using agents heterogeneity instead of more common decreasing marginal utility explanation. From such latter point of view one obtains the aggregate relationship by summing up the corresponding individual functions, but to obtain such individual demand curves one has to rely on a large number of assumptions (well shaped utility func-
Figure 5.2: The average (taken over all the TCs) daily price series $P_m$ (left panel). Scatter plot of price-quantity ($D_{Pm}, D_{qt}$) relation in differences (right panel). A unit of quantity is 1000 Kg.
tions, people find the solution of constrained maximization problems, and so on).
From the former it is possible to obtain the result using only agents heterogeneity. Think about a large number of buyers; each of them has to buy 1 unit of a good for which they have a reservation price. Their demand curve is vertical but with different heights. So, if for each level of price we sum the number of demanded goods we get a downward sloping curve. In this case one gets the same result using very few assumptions.

5.4.2 Price dynamics
To analyze the price dynamics during the day we show two types of graph. We first ranks the daily transactions by the time of day in which they occurred and then we perform averages for the transaction with the same rank. As shown in Figure 5.4 the average price goes down as the rank of the transactions increases. A strange regularity appears: for a large number of TCs the average price starts increasing for the last transactions, say $T$.
This apparent paradox can be understood linking the price
stopping rule followed by the buyers to the relationship between last transactions variation in price and the quantity of fish of the day. An optimal stopping (buy the fish) rule tell us that the value function to stop the price at time $t$ has a value $V_t$ satisfying

$$V_t = \max(U_t, E_t[V_{t+1}]) \quad (5.1)$$

where $U_t$ is the payoff function stopping at $t$ (say profits for buying the fish and satisfy customers’ demand) and the expectation is taken with respect to the $t+1$ probability distribution of results conditioned to $t$. When $U_t < E_t[V_{t+1}]$ it is better to wait.

For many buyers, arriving at the transaction $T$, may be optimal to buy even if the price is high when they have not reached the minimum quantity in order to satisfy customers demand. In such case, equation (5.1) becomes

$$V_T = \max(U_T, 0) \quad (5.2)$$

In days in which there is a low quantity of fish, the market equation (5.1) suggests that may be optimal to buy at higher than average prices starting from a number of transaction before the last one $T - i$ since with a limited supply it is likely that waiting for transaction $T$ will result in a difficulty to buy the needed fish. In other term $E_t[V_{t+1}]$ is low.

If the above explanation is correct we would expect a negative relationship between variation of prices in last transactions and daily supplied quantity ($q_t$). We perform regressions at different lag using the difference $P_{mT} - P_{mT-i}$. The result is particularly significant at $i = 2$. The limited-supply effect on last transactions can be shown in Figure 5.5 (left panel) where it is drawn the scatter plot of price variation for the last two transactions, $P_{mT} - P_{mT-2}$ versus daily quantity of fish $q_t$. The figure suggests that there is a threshold above an below which the last variations of prices and daily quantity relationship changes. We locate the threshold at $q_T = 2.8$ using the outliers test. The linear slope increases, in absolute terms, going from -0.4403 (the 95% confidence interval is [-1.13708,0.25701] so it is not statistically different from zero).
to -2.2648 (the 95% confidence interval is [-4.22589,-0.30377] so is statistically different from zero).

Another way to see the threshold effect is to use a non-parametric (kernel) regression drawn in Figure 5.5 (right panel). The regression shows a slope increase (in absolute terms) for daily quantity that are below 2.3.

To summarize, in the Ancona fish market the average price tends to increase for last transactions in days characterized by limited (compared to customers’ demand) supply of fish.

Another type of price dynamics analysis is shown in Figure 5.7. Here we plot the data corresponding to the day with the largest number of transactions for two TCs (the horizontal axis records the time of the transaction so a value of 4.5 means that the transaction took place at half past 4 in the morning).

It is evident in general that the price rises at the beginning and then settles down during the auction. This is due perhaps to the presence of buyers that have to buy very early in the morning for particular reasons (they may have a rather long trip back to their shops or they have restaurants and have to prepare the dishes and so on).

In Figure 5.6 we normalize the trading interval setting the starting minute to “t = 0” and the end of trading to “t = 1”.

Figure 5.4: Average price for each rank of transaction (the first dot on the left, for instance, is obtained collecting the price of the first transaction for each day and computing the average).
Figure 5.5: Scatter plot of price variation for the last two transactions, $Pm_T - Pm_{T-2}$ versus daily quantity of fish $q_t$. The left panel show a piecewise linear regression using the threshold $q_t = 2.8$ whereas in the right panel it is drawn a non-parametric regression with Gaussian kernel and bandwidth 0.4.
The graph shows the traded quantity by buyers leaving the market after a given time $t = \bar{t}$ (for example, there are 105 buyers over a total of 149 going out from the market after $t = 0.48$ and so 44 leaving before). The pattern suggests that the decline in demand is not linear. Instead there is an acceleration in the fall of the traded quantity at about $t = 0.4$.

Another question is the dependence of the price level on the day of the week.

In table 5.2 we re-compute the regression in table 5.1 adding 3 dummy variables for Tuesday (d2), Wednesday (d3), and Thursday (d4). As it is known, their values give the day effect compared to Friday. The table shows that the dummy variable for Tuesday is positive, meaning that the price is statistically higher than Friday. But then fall in Wednesday and Thursday (or, to be precise, do not rise since d4 is not significative) and then recovers (at least compared to Wednesday) in Friday even though do not return to the Tuesday level.

In other terms, fish is more expensive at the beginning of
the week while the “Friday effect” (families in catholic countries are used to eating fish on Friday) is not so evident (even though the price tends to increase compared to Wednesday). Lionel Robbins (1935) made the following remark about the reformation in the U.K which replaced catholicism with Anglicanisms, “The influence of the Reformation made no change in the forces of gravity. But it certainly must have changed the demand for fish on Fridays”.

<table>
<thead>
<tr>
<th></th>
<th>Coeff.</th>
<th>Std.Error</th>
<th>t-value</th>
<th>t-prob</th>
</tr>
</thead>
<tbody>
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<td>0.459</td>
<td>0.647</td>
</tr>
<tr>
<td>Dqt</td>
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<td>0.060</td>
<td>-5.300</td>
<td>0.000</td>
</tr>
<tr>
<td>d2</td>
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<td>0.194</td>
<td>2.570</td>
<td>0.011</td>
</tr>
<tr>
<td>d3</td>
<td>-0.505</td>
<td>0.191</td>
<td>-2.650</td>
<td>0.009</td>
</tr>
<tr>
<td>d4</td>
<td>-0.134</td>
<td>0.191</td>
<td>-0.705</td>
<td>0.483</td>
</tr>
</tbody>
</table>

Table 5.2: Regression of DPm versus Dqt with dummy variables for the day of the week. Tuesday (d2), Wednesday (d3), and Thursday (d4). Their value give the day effect compared to Friday.
5.4.3 Loyalty

A very interesting question is to ascertain whether the auction mechanism destroys buyer-seller relationships. Indeed Weisbuch et al. 2002 found evidence for loyalty of buyers to sellers in the Marseille fish market, but there the market is characterised by bilateral bargaining and the buyer could, in principle, collect every seller’s price to choose his best action. However many do not do so. Here Buyers learn to become loyal as in Marseille.

A statistical test for showing the (lack of) connection between buyers and sellers may be the chi-square test of independence between their respective distributions. To avoid the size-problem, i.e. the fact that buyers and seller trading more quantity are more likely to meet, we group buyers and sellers distribution in 2 and 3 groups that are homogeneous with respect to traded quantity. In other terms, buyers with id-number between 1 and 140 buy the same quantity of those between 141 and 303. Similarly, sellers are split in the two groups 1-82 and 83-154. For the 3 groups case, an homogeneous partition is: sellers = [1-95, 96-177, 178-303] ; buyers = [1-60, 61-111, 112-154].

The statistic of the chi-square test is 4.5752 (p-value = 0.032438) for the 2-groups case and 20.850 (p-value = 0.000339) for the 3-groups case showing that the hypothesis of random matching between buyers and sellers have to be rejected in both cases at 5% significance level and for the 3-groups case at 1% also.

Then we calculate the Gini index for each buyer\(^3\). In Figure 5.8 below we show the Lorenz curve for the two extreme cases (the least concentrated in the left panel and the most concentrated in the right one).

To have a global picture of the market we made a smoothed (Gaussian kernel) frequency distribution of the Gini index among buyers. A significant share of buyers have a Gini index equal to 0.4 and almost all have their index between 0.35 and 0.55.

\(^3\)The Gini index signals how a distribution is concentrated. In this case the index equals 1 if the buyer buys from only one buyer and equals 0 if the buyer buys from each of the \(n\) sellers he is a costumer a share \(1/n\) of the total fish bought.
The buyer-seller relationship is different from that in the Marseille fish market. There Weisbuch et al. (2002) find basically two types of agents: the loyal ones and the ones that do not care whom they buy from. The auction mechanism washes out the second kind of buyers since the distribution in Figure 5.9 is single peaked.

Further, we investigate the dependence of loyalty on buyer’s size. Figure 5.10 shows that the amount of loyalty increases with the size of the buyers up to a given value. Beyond this level the concentration index decreases or stay stable this is probably because very large buyers are forced to neglect the source of the fish if they want to gather enough.

5.4.4 Buyers and sellers price performance

The first question here is: are price performances related to the amount of fish transacted? Figures 5.11 and 5.12 provide an answer. Basically it seems that the amount of fish bought or sold have no influence on price performances. This conclusion is robust for buyers while for sellers we can observe that large ones never sold at an average price lower than 7, while some of the smaller sold at lower average price.

\footnote{Of course the quality of fish is also important for our analysis. Unfortunately there is no way to have this information from the dataset.}
Figure 5.9: Loyality.

Figure 5.10: Relationship between buyers size and their loyalty, each dot is a buyer.
Figure 5.11: Buyers price performances. All buyers (left), buyer with a purchased quantity lower than 4000 Kg. (right) this is basically a zoom on the low quantity of the left graphics.

Figure 5.12: Sellers price performances.
So to find out if there are some buyers that pay higher (lower) prices than others or some vessels getting higher (lower) prices than others we do a more sophisticated exercise. The analysis proceed as follows. For each subject (buyer or seller) we calculate the monthly average price and rank the subject by his price (prices are taken in increasing order). For each month, we thus associate the number one to the subject with the lowest price, two to the second lowest price and so on. Because the data cover 9 months, a subject that was always present on the market has a vector of 9 numbers attached denoting the ranks. If mister X has the vector [12,5,...] this means that there were eleven other people with an average price lower than his average price on September, 4 people having a lower average price on October and so on. To evaluate the performance of the subject we establish a threshold (for instance 10) and count the number of times the rank of the subject was less or equal to the threshold. In the following table we denote with $s$ the number of successes in this procedure, with $p$ the number of months he was present on the market. With $r$ we identify the rank of the subject if we consider the average price on all his transactions over the whole period and all TCs, the price column is the average price and quantity is the total quantity. So from the following table we can infer that buyer 271 was present for all the 9 months; all the 9 months his monthly average price was among the 10 lowest average prices. He bought 2991 Kg. of fish during the whole period at an average price slightly higher than 2 Euros and this was the 3rd lowest average price. Furthermore he had good results on the single TCs. For 8 months (over the 9 he was present) he had an average price among the ten lowest when he bought small sole (TC 12) and 4 out of 6 buying big hakes.
According to this table there are several buyers performing better than others even in particular TCs (for instance 164, 271, 153, 177, 169, 1).

In the following table we report the buyers with poor performance (they recorded a rank higher than 100).

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<td>6</td>
<td>9</td>
<td>12</td>
<td>3.522101</td>
<td>7129.71</td>
</tr>
<tr>
<td>259</td>
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<td>9</td>
<td>26</td>
<td>4.163261</td>
<td>317.77</td>
</tr>
<tr>
<td>169</td>
<td>6</td>
<td>9</td>
<td>16</td>
<td>3.678469</td>
<td>1449.74</td>
</tr>
<tr>
<td>1</td>
<td>5</td>
<td>8</td>
<td>13</td>
<td>3.579412</td>
<td>19177.11</td>
</tr>
</tbody>
</table>

According to this table there are several buyers performing better than others even in particular TCs (for instance 164, 271, 153, 177, 169, 1).

In the following table we report the buyers with poor performance (they recorded a rank higher than 100).

<table>
<thead>
<tr>
<th>id</th>
<th>s</th>
<th>P</th>
<th>r</th>
<th>price</th>
<th>quantity</th>
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<td>75</td>
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<td>9</td>
<td>148</td>
<td>22.65029</td>
<td>3599.64</td>
</tr>
<tr>
<td>84</td>
<td>9</td>
<td>9</td>
<td>130</td>
<td>10.96837</td>
<td>1125.12</td>
</tr>
<tr>
<td>270</td>
<td>9</td>
<td>9</td>
<td>144</td>
<td>18.58776</td>
<td>1261.83</td>
</tr>
<tr>
<td>106</td>
<td>9</td>
<td>9</td>
<td>145</td>
<td>18.71657</td>
<td>427.93</td>
</tr>
<tr>
<td>188</td>
<td>8</td>
<td>9</td>
<td>141</td>
<td>17.10356</td>
<td>2235.15</td>
</tr>
<tr>
<td>195</td>
<td>8</td>
<td>9</td>
<td>137</td>
<td>13.97355</td>
<td>1818.57</td>
</tr>
<tr>
<td>82</td>
<td>7</td>
<td>9</td>
<td>139</td>
<td>16.18111</td>
<td>1634.21</td>
</tr>
<tr>
<td>148</td>
<td>7</td>
<td>9</td>
<td>132</td>
<td>12.09021</td>
<td>947.61</td>
</tr>
<tr>
<td>156</td>
<td>7</td>
<td>9</td>
<td>140</td>
<td>16.46758</td>
<td>788.25</td>
</tr>
<tr>
<td>281</td>
<td>7</td>
<td>8</td>
<td>138</td>
<td>14.8035</td>
<td>3638.49</td>
</tr>
</tbody>
</table>

Buyers with high prices. There are buyer with very low performances (90, 91, 84).

The following tables are dedicated to sellers. The first ones indicates well performing sellers (that sell at high prices and have a high rank).
5.5 Conclusions

In this paper we investigate how the fish market of Ancona (MERITAN) works. As we pointed out in the introductory section fish markets have long been studied because they present a large range of allocating mechanisms (pairwise interactions, English auctions, Dutch auctions, etc.) and because of the perishable nature of the good exchanged. At the MERITAN, transactions take place by means of three simultaneous Dutch auctions.

The main question is how much the presence of a Dutch auction affect buyers’ behavior. Does it diminish the ability of a
buyer to perform well with respect to the prices of the transactions he makes? How do costumer relationships change under this price setting mechanism? Evidence from the data show that buyer-seller relationships are less evident than in a pair-wise bargaining market such as the Marseille Fish market but a remarkable amount of loyalty is still present under the auction mechanism.

The paper explains also the “declining price paradox” for the fish market of Ancona linking the price stopping rule followed by the buyers to the relationship between last transactions variation in price and the quantity of fish of the day. The average price tends to increase for last transactions in days characterized by limited (compared to customers’ demand) supply of fish.


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In this paper\textsuperscript{1} we perform an empirical investigation to detect if and to what extent agents’ behaviours depart from those foreseen by the standard economic theory in the Pescara wholesale fish market, which has a structure similar to the Walrasian one. We tackle the issue investigating features such as the dynamics of the structure of attendance in auctions, the varieties of fish presentation during the seller’s turn and the presence of long term relationships between buyers and sellers. We follow this way instead of focusing on the price dispersion and dynamics to avoid risking that the unobserved quality differences of the traded products might bias the results of the analysis.

6.1 Introduction

Classical economics depicts markets as places where prices move freely to equate the demand and supply. More precisely, the price is the sole variable affecting agents’ behaviour and

\textsuperscript{1}We thank the Resal software staff which is collecting the data and delivered us a high quality dataset. The fish market coordinating staff, in particular Antonio Ciriaco, spent a considerable amount of time giving us additional information that were not included in the dataset. We gratefully acknowledge helpful comments by the participants of the workshop “The Emergence and Impact of Market Institutions: The Market for Fish and other Perishable Commodities”, Tromsø (Norway), 5-6 July 2007.
before exchanges become binding they are moved (by the Walraskan auctioneer) and agents are allowed to resubmit their proposals until buyers’ and sellers’ decisions are compatible. Although this way of thinking is very useful from a theoretical point of view, allowing economists to build impressive formal models, the reality delivers us a rather different picture: the above sketched tâtonnement process is not implemented in any real market. This pushes economists to question to what extent existing market structures are good devices to attain optimal allocations. The outcome of these investigations is a huge body of literature that, among other topics, includes bargaining theory (Osborne and Rubinstein 1990, Muthoo 1999), auction theory (Klemperer 2000, 2004) and the more recent field investigating the relationships between market structure, individual rationality and the global outcome (see among others Gode and Sunder 1993, Domenech and Sunder 2000, Kirman 2004).

Besides the theoretical issues, empirical investigations help us understanding how markets function. Recently a number of studies have concentrated their attention on financial markets which function in a similar way to the theoretical case. They show results that are far from the expected ones (McCauley 2004, Mantegna and Stanley 2000, Levy 2006 are examples). Despite the considerable amount of financial market organisation, the special nature of the objects of transactions could not be sufficient to give arguments to rethink in a critical way all the standard economic constructions.

A very interesting issue arises from analysing retail markets where products of everyday use are exchanged. These markets have not been studied because data is not available (think for example of an outdoor local market). The difficulty of collecting data may be overcome in wholesale markets where sellers (and rarely the management trust) record data from each transaction. Especially for perishable products, wholesale markets actively operate in all large cities and often in smaller realities. Besides the availability of data, markets for perishable products are also interesting because of a number of reasons (Kirman 2007). Firstly, an explanation for why apparently similar markets have different structure (bilateral bargaining, ascending or descending auction), as happens for
fish markets, is needed. Secondly, markets for perishables are kept in a clearing condition by the fact that stocks cannot be carried over. This feature makes them a good candidate for comparison with the theoretical case. Thirdly, the property just mentioned removes the presence of phenomena like intertemporal substitution, making the empirical investigation of the individual behaviour simpler. In this work, we mainly take advantage of the last point because we focus on agents' behaviour.

Although descriptions of such types of market come from the Greek and Roman periods, the recent scientific works on the topic are not so numerous. Kirman and Vignes (1991), Härdle and Kirman (1995), Weisbuch, Kirman and Herreiner (1998), Kirman and Vriend (2000) investigate the Marseille fish market; Graddy (1995, 2006) the Fulton fish market in New York and Kirman et al. (2005) the Marseille fruit and vegetable market. In a wholesale market, professional agents operate and a market with well-informed buyers and sellers should also be a very competitive one. The above mentioned papers show how similar markets are characterised by patterns of behaviour which may suggest imperfect competition and a segmented market; in fact, buyers in these markets act like agents for customers with very different elasticities of demand and the repeated nature of bargaining as well as extensive knowledge of the sellers may have created the basis for tacit collusion and allowed the dealers to gather economic rents by exploiting the different elasticities and buying patterns (Graddy 2006). In the papers analysing the Marseille fish market the authors find the presence of a significant level of loyalty from buyers to sellers. These long term relationships could also prevent the attainment of a situation of perfect competition. Therefore, as in the financial markets case, different results from those foreseen by the standard economic theory are detected. In all the cited works, however, the analysed markets greatly differ from the ideal theoretical market because their exchanges take place after a bilateral bargaining process instead of being the outcome of a centralised process.

On analysing the Pescara² wholesale fish market (MIPE, that

²Pescara is a medium size Italian city situated approximately in the middle of the
in Italian stands for Mercato Ittico PEscara), this paper aims to contribute towards this strand of literature. The present work differentiates itself from the cited literature in two aspects: first of all, the market under investigation has a centralised structure organised as a Dutch auction. From this point of view, our situation is closer to the theoretical one than that analysed in previous works. Secondly, we marginally rely on the observed prices to avoid the effect of unobserved qualitative differences. We perform an empirical investigation to detect whether and to what extent agents’ behaviour departs from those foreseen by the standard economic theory in the more “Walrasian” market structure of MIPE.

The paper is organised as follows. After the description of the market (section 6.2), we examine in turn the behaviour of sellers and buyers. For the former (section 6.3) we intend to analyse the decisions on their weekly schedule structure and on the sequence of varieties during an auction. The questions we want to answer are: are there preferred structures? If yes, are they rationalizable? Are sellers exploring new strategies?

In analysing buyers (section 6.4) we focus on a different and very interesting topic: the buyer-seller relationship. The main goal of this section is to identify the presence of buyers’ loyalty on the analysed market. Section 6.5 presents some concluding remarks.

6.2 Market description

The MIPE is organised as two simultaneous Dutch auctions. We shall refer to the three types of agents operating on the market as sellers, buyers and auctioneers. Sellers are the trawler owners who bring the fish to the market after catching it in the nearby sea. Buyers buy the fish to sell it in turn to the final consumers, to supermarkets or to transform it (cooking or making ready-to-cook products). Finally, the auctioneers direct the transactions and decide the initial price for each case of fish (products are arranged in cases of 4-5 kilos).

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Italian east coast.
6.2.1 Description of a typical session

Before the beginning of the auction, sellers are randomly selected and each of the first two is assigned to either of the two conveyor belts crossing the market hall. When the belts start moving, the selected sellers put the cases on one end of the assigned belt and the cases flow slowly towards the other end. Each case still unsold stops on the automatic weighing machines located in the middle of the conveyor belts. The auctioneers move the fish to let the buyers also see the fish lying in the bottom of the case; they often take a fish from the case and show it to the attenders. The auctioneers communicate to the cabin operators (each of the two auctioneers stands by a cabin where a person is managing the market information system on a computer), the fish variety and the initial price. The cabin operators manage the displaying of the seller’s name, the fish variety and the initial price on the two large screens. The price counter starts going down on the display. Buyers are endowed with a remote control which is able to stop the counter. The buyer who stops the counter gets the case and, if the cases which follow contain the same variety, the buyer is asked by the auctioneer how many cases he would buy for the same price. Whenever a seller finishes, the next seller starts loading onto the free conveyor belt. As a result, all the cases of the same seller run sequentially on the same conveyor belt.

6.2.2 Data set

The dataset contains data from October 3rd, 2005 to May 18th, 2007 and records, for every transaction:

1. date and time;

2. product, buyer and seller’s identification number;

3. the quantity (weight in kilos), price per kilo and number of cases;

4. the conveyor belt identification number.

In the analysed period, 59 sellers and 132 buyers operate 261055 transactions on 72 varieties for a total amount of 1974316 kilograms of fish exchanged. The market operators
meet once or twice in the working-days and extraordinarily on Saturday. More precisely, the Monday auction takes place in the afternoon (the only exception is February 27th, 2006 when it took place also in the morning). On Tuesday, the market opens regularly both in the morning and in the afternoon. On Wednesday, it took place morning and afternoon until August 30th, 2006. Since this date, the Wednesday auction has taken place in the afternoon (the only exceptions are December 6th, 2006 when it was held also in the morning and December 12nd, 2006 when it was held only in the morning). On Thursday, the market opens regularly both in the morning and in the afternoon. The Friday auction has taken place in the morning starting since September 1st, 2006, and occasionally in the afternoon during Christmas time (December 23rd, 2005, December 22nd, 2006 and December 29th, 2006). On Saturday, the auction took place only three times during Christmas 2006 (December 23rd, 2006 morning and afternoon, and December 30th, 2006 in the morning).

We point the reader to Figures 6.1 and 6.2 to have a global picture of the market. Figure 6.1 gives a kernel estimation of the size distributions for buyers and sellers. It shows how buyers are smaller than sellers, however a number of them have a significant size. Sellers are less concentrated and they do not have a prevalent size. Similar results are detected on the Ancona fish market by (??).

Figure 6.2 depicts the dynamics of the weekly quantities and the quantities exchanged in the weekday auctions. From this figure one can detect that the weekly quantity exchanged in the considered period oscillates between 10 and 40 tons. The Monday and Wednesday afternoon auction sell a limited amount of fish, while the most important section is the Tuesday morning one. On Thursday agents gradually shift their preference from the afternoon to the morning section. Finally, The Wednesday morning section was moved to Friday morning since August 2006.

We gather very useful information by asking the fish market coordinating staff. From these discussions came out that

\[3\] The three largest buyers bought 265749.10, 143163.20 and 125117.50 kilograms respectively.
during the analysed period the market was subject to non negligible perturbing events. For example, as we noted above commenting on figure 6.2, the Wednesday morning auction was replaced by that on Friday morning in August 2006. In addition we were told that this change was due to the trawler owners because the large amount of fish available on Tuesday, Wednesday and Thursday pushed the price to a low level.

In these interviews we talk about the economic gain of the auctioneers. They are paid by sellers the 1% of the total value of sold fish. The auctioneer makes an additional gain by taking occasionally a fish (that he particularly likes) from the case at hand and taking all the gathered fishes with him at the end of the auction. This happens before the case is sold and the seller bears this cost.

The market staff were very patient to classify fish varieties, buyers and sellers for us. For each of the 72 varieties they indicate if it can be classified as cheap, average or more expensive. For sellers they indicate their size (small, medium, large) and a subjective evaluation of the quality of the fish they bring to the market. The most useful work was the classification of buyers for whom they indicate the type of activity (pedlars, fish shop owners, restaurant owners, ready to cook producers, wholesalers) and the distance of their working place from the market.

Given this amount of information, many different investigations are possible. As mentioned before, we concentrate here on the buyers and sellers’ behaviour leaving other interesting issues (like the price dynamics and dispersion, the price-quantity relationship) for future works. In the following analysis we discard data from the Christmas periods during which the market might not work in a regular way.

6.3 Sellers

Sellers have to take two decisions on their everyday activity: firstly, they have to decide in which of the auctions they want to participate and consequently organise their fishing days. Secondly, at the market, they have to decide the sequence of cases (fish varieties) to appear on the belt when it is their
turn. We shall attempt to infer their behaviour from the data; in particular we want to find out whether they decide at random, they follow rules of thumb or they implement strategies; whether sometimes they search for better behaviour or whether their behaviour changes with their size. Furthermore, we shall exploit the possibility offered by our data to investigate sellers’ reactions to a perturbing event like the change of the weekly auction schedule mentioned above.

Let us discuss in turn some evidence on the two above mentioned sellers’ decisions.

6.3.1 Auctions’ attendance and reaction to shock

First of all, we discuss if sellers take part at the auctions in the morning or in the afternoon.

We denote with $q_{jm}^m$ the quantity sold by the seller $j$ mainly in the morning (of the whole period) and with $q_{ja}^a$ the quantity sold by the same seller in the afternoon. $q_j = q_{jm}^m + q_{ja}^a$ is of course the total quantity sold by $j$. The difference $q_{jm}^m - q_{ja}^a$ is positive if $j$ sold more in the morning than in the afternoon. Figure 6.3 shows how this value can change with the sellers’ size (the figure reports in the horizontal axis the rank of sellers sorted in increasing size order). The sellers can be classified into three groups: the small ones (with rank lower than 15) have all but one a negative value, it means that they attend mainly the afternoon auctions; the large ones (with rank higher than 46) have a sharp tendency to sell in the morning sessions; medium size sellers have a mixed behaviour. In Figure 6.4, where the previous difference is divided by the total amount of fish sold by the seller, one can make this behaviour more evident.

A more informing exercise consists on evaluating, for each seller, the dynamics of its attendance schedule. Having reached this goal we could try to detect if sellers have preferred structures of weekly attendance, if they experience from time to time new opportunities and how they react to perturbing events like the one we mentioned in the previous section. We do this by evaluating the presences in each week in the following way: for each week we build a binary vector of 8 elements. The first 4 elements contain the indicators for the
morning auctions (Tuesday, Wednesday, Thursday and Friday): 0 if the seller was not present and 1 if he was present. The last 4 are for the afternoon auctions (Monday, Tuesday, Wednesday and Thursday). We voluntarily avoid the Monday morning, the Friday afternoon and the Saturday occasional sections to evaluate the regular behaviour of sellers. For example, we have considered the following attendance vector for a seller in a particular week $1, 0, 1, 0, 0, 0, 1, 0$. This does mean that the seller attended to the Tuesday morning, the Thursday morning and the Wednesday afternoon auctions. The decimal representation of a $z$-dimensional binary vector is a one to one correspondence from $\mathbb{B}^z$ to the set $\{0, 1, \ldots, 2^z - 1\} \subset \mathbb{N}$ where $\mathbb{B} = \{0, 1\}$ and $\mathbb{N}$ denotes the natural numbers. In the mentioned example, the corresponding natural number is 162. Obviously this number increases with the number of presences: it is high for sellers attending to the morning auction and it is low for those who attend to the afternoon ones. On calculating this value for a particular seller in subsequent weeks and on analysing the time series, we are able to obtain information about his behaviour. In Figures 6.5 and 6.6 we report such exercises for two sellers (we shall refer to them conventionally as buyer 2 and 15 because this is their rank according to the amount of fish purchased - in decreasing order). These sellers were selected to show how very different agent behaviours co-exist in the market (below, we overcome the arbitrary nature of this choice by plotting all the buyers’ binary index in Figure 6.7). The figures show, first of all, that sellers have in general one or a number of preferred strategies. For most sellers, the change of the fishing schedule (signalled in the graphs by the vertical line) modified the set of preferred strategies. Seller 2, whose behaviour is shown in Figure 6.5, is an interesting case. Here we propose a possible interpretation of his behaviour. He experienced a new strategy highlighted with the dashed box A, but probably it had negative results because he never used it again; he had a period in which he looked for new strategies (box B) at the end of the observed period. Seller 15 is almost exclusively present in the afternoon auctions. He has a preferred strategy that was not affected by the timetable change. The other adopted strategies seem to be chosen randomly. As regards the whole set of sellers, there are some strategies
Figure 6.1: Kernel density estimation of buyers and sellers size (in kilos) distributions.

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>binary</td>
<td>decimal</td>
</tr>
<tr>
<td>1,1,0,0,0,0,1</td>
<td>193</td>
</tr>
<tr>
<td>0,0,0,1,1,1,1</td>
<td>15</td>
</tr>
<tr>
<td>0,0,0,0,1,0,1</td>
<td>5</td>
</tr>
<tr>
<td>1,0,1,0,0,0,0,0</td>
<td>160</td>
</tr>
<tr>
<td>1,1,1,0,0,0,0,0</td>
<td>224</td>
</tr>
</tbody>
</table>

Table 6.1: The most used strategies before and after the change in the fishing schedule.
Figure 6.2: Weekly and weekdays time series of the exchanged quantities (Kg).

Figure 6.3: Rank of sellers sorted in increasing size order vs. $q_j^{m-a}$.

Figure 6.4: Rank of sellers sorted in increasing size order vs. $q_j^{m-a}/q_j$. 
Figure 6.5: Weekly sequence vs. decimal representation of the attendance vector for the 2nd largest seller.

Figure 6.6: Weekly sequence vs. decimal representation of the attendance vector for the 15th largest seller.

Figure 6.7: Binary index dynamics for all the sellers.
that individuals use more than others. These results are presented in table 6.1 where sellers that were absent in more than 1/4 of the weeks in the considered period are discarded. Before September 2006 the most used strategy by 10 sellers was to participate in the Tuesday morning, the Wednesday morning and the Thursday afternoon. More generally, among the 5 most used strategies, three of them consist in attending prevalently in the morning and two exclusively in the afternoon. After August 2006, there was a large adoption of one strategy as the most used (18 sellers) and a large fraction of sellers has been attending one of the morning auctions (now the 2 most used strategies provide for a presence in the morning). The afternoon strategies are still there although adopted by a smaller number of agents. A visual representation of this fact is reported in Figure 6.7 where we pool the data for all the sellers.

Moreover, discarding the sellers with a low attendance rate still once, we evaluate for each seller how often the three most used strategies were adopted. Figure 6.8 reports in the horizontal axis the share signalling how often the three most used strategies are used by a buyer and in the vertical axis the estimation of the buyers density; it shows that a large part of sellers use one of the three preferred strategies in about half of the weeks he participated during the period October
2005 - August 2006. The percentage increases sharply in the
time span September 2006 - May 2007. The strategies used
just once (Figure 6.9) have their mode in correspondence of
about 10% of the weeks and had a slight increase in the period
September 2006 - May 2007.\footnote{More formally, let $n_{ij}$ be the number of weeks the strategy $j$ was used by buyer $i$, and $n_i = \sum_j n_{ij}$. We compute the shares $\alpha_{ij} = n_{ij}/n_i$ and denote with $r$ the rank of strategies when $n_{ij}$ is sorted in a decreasing order. The horizontal axis of Figure 6.8 reports $\sum \alpha_{ij}$ taken over the $js$ that satisfy the condition $r \leq 3$. The horizontal axis of Figure 6.9 reports $\sum \alpha_{ij}$ taken over the $js$ that satisfy the condition $n_{ij} = 1$.}

According to these results, it seems reasonable to conclude
that sellers (apart from some exceptions) are not behaving
randomly. They rather probably “play” some mixed strategy.
Furthermore, they seem to be able to find their behaviour
after an anticipated structural change.\footnote{The change of the weekly auction schedule was decided by sellers that consequently had time to evaluate how to react to this change.}

6.3.2 Varieties of fish presentation during the
seller’s turn

In this section we want to detect whether there is a prevailing
pattern in the sequence of varieties proposed by sellers. Are
cases presented randomly or arranged in a particular way?
Are cheap varieties presented before or after the more expen-
sive ones? And if there is a particular pattern, is it a justifiable
adoption from the economic point of view?

According to economic considerations, the sequence of va-
rieties presentation should be chosen in order to maximise
the sellers’ revenue from sales, that is in order to maximise
the degree of competition among buyers. In an ideal market
with perfectly informed rational agents everything is known
(at least in a probabilistic sense) at the beginning and conse-
quently the degree of competition on every case of fish should
be the same regardless of the point in time it appears. Thereby,
in the ideal case just described, one should observe varieties
appear in a random order.

Let us concentrate on the time series of the prices per kilo ob-
tained by a particular seller in a particular auction. When an
increasing trend in this data is detected it means that cheap
fish is presented first. We try to detect this increasing trend in
the following way: we take the transactions of a seller (say \(j\)) in a particular auction and we compute the average price \(\bar{p}_{ja}\) (the lower script \(a\) indicates that the mean relates to an auction). Then we divide these transactions into two groups: the first half of the early (\(e\)) transactions and the second half of the late (\(l\)) transactions. For both the subsets we compute the average price \(\bar{p}_{ja}^e\) and \(\bar{p}_{ja}^l\). For each seller, in each of the auctions in which he was present we compute the ratio \((\bar{p}_{ja}^l - \bar{p}_{ja}^e)/\bar{p}_{ja}\) that, if positive, signals higher prices for the second half of the sales. The total number of auctions which took place in the analysed period is 485. The seller who attended most has rank 13 in size and attended 251 times. We considered the sellers who attended more than 50 times (48 of the 59 sellers remain in the sample). For each of the selected sellers we build a time series collecting in a chronological order the indexes for each of the auction he attended. Since the calculated ratios are largely dispersed, we apply the LOWESS (local weighted smoothing) algorithm to smooth the data (we set the parameter to 1/5, that is for the local evaluation a window containing 1/5 of the considered data is used). Classifying sellers according to the minima and maxima of their smoothed curves we detected a tendency by the sellers to present the cheap fish before the more expensive one: 35 sellers have the minimum of the smoothed curve greater than 0 (Figure 6.10 depicts the situation for the seller with the highest minimum). Only one has the maximum of the curve lower than 0 (Figure 6.11).

To have a global picture we compute for each seller the average of \((\bar{p}_{ja}^l - \bar{p}_{ja}^e)/\bar{p}_{ja}\) over all the auctions he participated in. In Figure 6.12 this average index is plotted against the rank of the seller (sorted in an increasing size order). Two fitting lines, obtained using linear and non parametric regression, are also drawn. The result of the linear regression is reported in the table hereunder.

| coefficients | Estimate | Std. Error | t value | \(Pr(>|t|)\) |
|--------------|----------|------------|---------|-------------|
| intercept    | 0.803261 | 0.098360   | 8.167   | 3.64e-11    |
| slope        | -0.008026| 0.002851   | -2.815  | 0.00669     |

This investigation shows how sellers, especially small ones, present the cheap varieties before the more expensive ones. At this point we wonder: is there a rationale for this behaviour?
Figure 6.10: Seller with the highest minimum of the smoothed curve (each dot is an auction in which he participated).

Figure 6.11: Seller with the lowest maximum of the smoothed curve (each dot is an auction in which he participated).

Figure 6.12: averages of $(\hat{p}^i - \hat{p}_a)/\hat{p}_a$ over the auctions (each dot is a seller) and fitted values using linear and non parametric regression. Horizontal axis: rank of sellers sorted in increasing size order.

Figure 6.13: Horizontal axis: waiting time in minutes between cases of mantis prawn. Vertical axis: difference in prices (€) per kilo of the two cases used to calculate the waiting time.
From the economic point of view it is convenient to delay an action if one has an option value to wait. One possibility to check the existence of this reward is to verify whether the prices increase with the waiting time. Let us assume to have a case of variety $f$ which appears at time $t_1$ and it is sold at $p_{ft_1}$ and the next case of the same variety appears at time $t_2 > t_1$ and it is sold at $p_{ft_2}$: is there a positive relationship between $p_{ft_2} - p_{ft_1}$ and $t_2 - t_1$? After doing this experiment on several varieties, the answer at this question seems to be negative (Figure 6.13 shows the results for the mantis prawn). However, we cannot conclude that this behaviour is not rationalizable from the economic point of view. It is plausible to think, for example, that buyers’ arrival times are such that the degree of competition is low just at the beginning of the auction and then it gradually increases. In this case, it is rational for sellers to avoid presenting the expensive fish first because, otherwise, the few present buyers would let the price go down to buy at a very convenient condition. This will end up in a low revenue in the case the seller was the first one to load the belt. Unfortunately, we have no way to obtain from the dataset the evolution of the degree of competition at the beginning of the auctions; so the sketched explanation remains a conjecture.

As pointed out by our previous exercise on the weekly auction attendance, in this paper we also focus on the dynamics of the agents’ behaviour. Now we want to verify if sellers change their strategy about the presentation in time of varieties. We do it using again the smoothed curves in Figure 6.10 and 6.11 and looking at the values they assume in correspondence with their maxima and minima. In fact, a change of sign between these values probably testify a change in the seller’s behaviour. The result of searching such events on the whole set of sellers reveals they are rather static. Two exceptions are shown in Figures 6.14 and 6.15.

6.4 Buyers

Buyers can of course decide which of the auctions to attend. A similar analysis is possible as regards what we made for sellers. However, buyers are constrained by the final demand
that is supposed to have a rather regular flux, so their attendance is expected to be regular. We prefer to focus on a more stimulating and interesting issue concerning the relationship between buyers and sellers (Weisbuch, Kirman and Herreiner 1998, Kirman and Vriend 2000). Are buyers fully exploiting the opportunities offered by the market, given that they are not influenced by the seller identity? Of course a positive answer to this question excludes the presence of sellers’ market power giving argument to state the market has a potential to approach a perfect competition state. Indeed, the positive answer to the previous question is the expected one. The market is centralised and no leather shoes costs must be sustained by buyers to gather information from all the sellers. Furthermore, information asymmetries should not be a problem since the buyers are fully informed about the available quantity and they are perfectly able to evaluate the quality of the fish.

In the following steps we analyse this issue trying to detect the degree of loyalty from buyers to sellers. First of all, we check whether buyers buy randomly or adopt some strategies. In the second step, we try to detect the presence of loyal buyers searching for those buying from a reduced number of sellers.
6.4.1 Random vs. strategic behaviour

The goal of this section is to establish, for each particular buyer, if he cares or not about the identities of sellers. In doing that, we have to keep in mind that sellers are heterogeneous and have different sizes. In the following analysis, we refer to a buyer that does not care about the sellers’ identities as a random buyer. Basic probability theory tells us that for a random buyer, the share of fish he buys from a seller should be asymptotically equal to the market share of the seller. Having this in mind, we compare for each buyer the distribution of the quantity of fish bought from each seller he uses with the conditional distribution of the size of sellers. For the latter distribution, conditioning is on the fact that the seller is among those the buyer bought from. This choice is justified by the fact that buyers attending prevalently the morning (afternoon) auctions meet rarely sellers who are there prevalently in the afternoon (morning). More formally, let $k_{ij}$ be the amount (kilos) of exchanges between buyer $i$ and seller $j$ in the whole period; $\Omega_i$ the set of sellers buyer $i$ uses and $k_j$ the total amount sold by seller $j$. Then we compare

$$\frac{k_{ij}}{\sum_{j \in \Omega_i} k_{ij}} \quad \text{with} \quad \frac{k_j}{\sum_{j \in \Omega_i} k_j}.$$  

Doing a scatter plot, for a random buyer the coordinates formed by these two shares should locate approximately along the 45 degree line. For each of the 130 buyers (two buyers were discarded because they bought from less than 5 sellers a very small quantity) we evaluate this probability plot by means of a linear regression. According to our reasoning, a random buyer should have a significant slope coefficient whose value is close to one. The result of this experiment is summarised in Figure 6.16 that reports on the horizontal axis the size of the buyer taken in an increasing order and in the vertical axis the values of the slope coefficient. A count of the dots reveals that 92 buyers have a slope coefficient significant at 1% (identified by a ○ in the figure), 5 at 5%, 6 at 10% and 27 buyers have a not significant slope coefficient (the • in the figure).

To group the population of sellers we use the slope coefficients regardless of their significance level. The internal minimum of
the estimated kernel density distribution obtained using the optimal bandwidth gives us an objective threshold to classify buyers into groups. The value of the minimum is 0.53 (the dashed line in Figures 6.17 and 6.16). Considering a symmetric interval around 1, we can set the upper bond to 1.47 (the dotted line in Figures 6.17 and 6.16). According to this classification scheme we have 87 random buyers and 43 buyers who implement an unknown strategy. In the Pescara fish market, 2/3 of buyers can be classified as random.

6.4.2 Loyalty

On the base of previous considerations, we know that a number of buyers do not buy randomly. How can we go one step further and investigate the presence of loyalty? A possibility to detect this is to start from the observation that loyal buyers buy from a low number of sellers. The main difficulty here is given by the heterogeneity in size of the buyers. So, to detect when a number of sellers is low for a buyer, we should determine which is the “theoretical” number of sellers the buyer should use given his size. In other words, we need a term of comparison. Using again the idea of random buyer, one way to obtain the term of comparison is by using the multinomial
distribution. To be more formal, let us denote $t_{ij}$ the number of transactions between buyer $i$ and seller $j$. Buyer’s $i$ and seller’s $j$ total number of transactions are

$$t_i = \sum_j t_{ij} \quad \text{and} \quad t_j = \sum_i t_{ij} \text{ respectively}.$$  

Using the multinomial distribution, the theoretical number of transactions between $i$ and $j$ is:

$$t^*_{ij} = t_i \frac{t_j}{\sum_j t_j}.$$  

Knowing this distribution for each buyer we can also compute the theoretical number of sellers which the buyers would buy from. In fact it is given by

$$n^*_i = \sum_j \Theta_{ij}$$

where $\Theta_{ij} = 1$ if $t^*_{ij} \geq 1$ and $\Theta_{ij} = 0$ if $t^*_{ij} < 1$.

We compute this theoretical quantity for the buyers in our sample and we compare them with the value computed from the data ($n_i$). Figure 6.18 shows the results.

We perform a two-sample Kolmogorov-Smirnov test to check whether the the two distributions are identical. The test yields a $D$ statistic equal to 0.4308 with an associated $p$-value of 6.676 · $(10)^{-11}$. The null hypothesis of equal distributions ($H_0 : D = 0$) cannot be accepted at any reasonable confidence level. This outcome is in favour of the presence of loyalty. Taking into account this result and those obtained on the Marseille fish market (Weisbuch, Kirman and Herreiner

Using the multinomial distribution is not the only way to obtain the values we are interested in. An alternative way is to resort to Statistical Physics. Suppose you have a system of $t_i$ particles in which each of them can take an energy level $j \in \{1, 2, \ldots, J\}$. Denote with $t_j$ the degeneracy of energy level $j$. The question is: which is the most probable number of particles to be found in each energy level? The answer to this question is given by what is known as the Maxwell-Boltzmann statistics. Considering only the number of particles constraint, the solution is: $t^*_{ij} = t_j e^{-\alpha_i}$ with $\alpha_i = \ln \left( \sum_j t_j \right) - \ln(t_i)$. Indeed, the standard problem leading to the Maxwell-Boltzmann statistic has the additional constraint that the system must have a fixed energy (see (? ) or any handbook of statistical physics). (70 ) p. 17 has precisely the solution with the only constraint on the number of particles.
1998), it seems that customer relationships are there whenever the sellers’ identity is publicly known regardless of the market organisation. An interesting issue is whether the presence of loyalty is due to sellers’ qualitative differences or it is due to other phenomena as for example buyer’s inertia. Unfortunately, the available data do not let us delve into this matter.

6.5 Conclusions

Using a detailed data set, we have investigated in this paper the buyers’ and sellers’ behaviour in the Pescara fish market. The market has a centralised structure and it consists in two simultaneous Dutch auctions. The presence of an auctioneer and that of a limited number of well informed buyers makes the situation of this market close to that of a theoretical Walrasian market. So it seems an opportunity to check whether the outcome of a real market like the one at hand is close to
that foreseen by the economic theory. Differently from the existing literature, we tackle this issue directly analysing the agents’ behaviour instead of using consideration about prices. This is because we prefer to avoid risking that the unobserved quality differences of the traded products within the same category might bias the results of the analysis. We investigate sellers’ main decisions: how they organise their weekly fishing schedule and how they decide the sequence of cases (fish varieties) to appear on the belt during an auction. It can be observed that sellers use in general a restricted number of strategies in deciding their weekly fishing schedule giving reason to think they are implementing a sort of mixed strategy. We find examples of sellers whose behaviour can be interpreted like that of a person experimenting with new opportunities. The practise to present cheap fish before the expensive ones detected in the data is not rationalizable by the presence of an option value to wait along the whole duration of the auction, but we conjecture it could be justified by the presence of such a value at the very beginning of the exchanges. Concerning buyers, for each of them we build the transaction structure he would have had if he had bought without caring about the sellers’ identity. After comparing their real behaviour with this benchmark case we verify that a certain degree of loyalty is still present in a centralised market organised as a sequential Dutch auction like the Pescara fish market.

The existing literature points out that the presence of buyers looking for new strategies, buyers’ loyalty to sellers and non rationalizable behaviours are symptoms that indicate the particular market structure under scrutiny is not properly functioning at least from the mainstream economics point of view. Overall, our analysis reveals the above mentioned phenomena are present in the Pescara market. Even if their intensity is not so strong as in Marseille, we should not underrate their existence. It could be the case their importance would dramatically increase as soon as we move from the special case at hand. So, our results can be viewed as the onset of the phenomena observed on a centralised market where a huge number of agents participate as in the financial markets or those observed in markets without a centralised structure like
the Marseille fish and fruits and vegetables markets. In other words, the fact that we investigate a special case strengthens the opinion that the regular working of markets, especially thick and dynamic ones, significantly departs from the archetypal.


Aspects of a perishable market in an agent-based model
Juliette Rouchier (CNRS-GREQAM, Marseille)

In this paper we present two aspects of an ongoing work dealing with the representation of professional markets along a supply chain. The paper starts with a description of the market that was observed for some months and the stylized facts that were abstracted from it. The paper presents the model of market that was built after field study was conducted, and a first model was criticised by academics and by market actors. This new model describes the emergence of niches for sellers, due to the lack of supply they experience when their buyers come to get goods. The ratio of opportunistic and faithful agents among buyers is shown to have an impact on the learning of sellers. This paper describes an application of multi-agent systems to economics. The issue we address in our work is the actual functioning of a distributed market in terms of information acquisition for agents. We show here possible links between individual information acquisition and global results in the fluidity of exchanges. A multi-agent model has been built on the basis of field observations and interviews led at the Marseille Fruits and Vegetables wholesale market in 2002-2003. Two types of artificial agents

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interact, wholesale sellers and retailers, surrounded by an environment of exogenous supply and prices. Retailers can choose wholesale sellers according to two logic: either following some relational loyalty or searching for best prices (which takes time). We study the influence of the number of loyal buyers to see the importance of both categories in the good supply of consumers and the limitation of garbage.

7.1 Introduction

In markets, the individual behaviours and lie behind market dynamics are often badly known. It is shown that once we know all reservation prices (what buyers are willing to pay and sellers willing to get) it is easy to decide of the set of interactions which will generate the highest surplus. However, the actual process that does lead to a stabilisation of prices is not so well informed (Kirman 2001). Indeed the encounter of offer and demand, that sets the prices, is a quite abstract image when describing multiple actors with limited information. It is thus legitimate to take a step-by-step perspective and consider individuals dealing with the unknown with diverse strategic or routine-based behaviours. Numerous studies have already been led on that issue, focusing on the actual information processing and learning that individuals use. This includes field observations (examples are in: Galtier et al. (2002), Tarrius 2002), experimental observations (Smith 2002) and computer based simulations (Tesfatsion and Judd 2006). Some of these studies in artificial systems stress the idea that economic actions are not necessarily led by the optimising rationality of economic theory, but rely on complex learning processes (Brenner 1999). The knowledge of real logic is important if one takes the perspective of a potential action on the system (market design or political advises), because the emergence of global data are really dependent on the individual actions (Janssen and Jager 2001). Agent-based simulation allows a representation of market that is relevant to take into account a very usual situation in these exchange in-
stitutions: decentralisation of actions and distribution of knowledge (Kirman 2006).

One field has been quite largely explored in this area, since it displays interesting features for researchers: perishable good markets. Perishable goods are interesting because it is possible to analyze settings where goods are sold without considering stock management and because there is a limitation in time for the acquisition of goods. These characteristics allow to consider interactions that take place in a limited time, with a very costly constraint for agents to provide a good (for sellers) and to acquire it (for buyers). Another aspect of perishable good markets is that buyers have a high incentive to get fresh goods and hence to be present every day on the market: they tend to learn how to behave from one day to another.

In this paper we present a model describing a market in which buyers and sellers interact in the long-term. Several results have been found in the study of this model, and here we insist on the role of loyal buyers in the anticipation of stock for sellers. The market was inspired by our observations on the Arnavaux market, which had already been used as a based of a preceding model. This model has been corrected due to remarks by academics and the wholesaler we mainly interacted with. In its last form it represents buyers and sellers who interact on resources defined by two qualities, each quality being defined by two prices. A buyer can be faithful or opportunistic: the former go regularly to see the same seller and only have a long-term evaluation of their relations that gives a weak feedback of unsatisfaction to the seller; the later always select the sellers that interest them most at one time-step. Buyers can be interested in getting good quality or cheap prices, and each seller tries to get specialised in either good quality or cheap products depending on the type of demand. The model is presented, as well as basic evolution of simulation. The ratio of faithful and opportunistic agents is shown to have an important impact on the global learning that takes place in time on our artificial market. Also, the influence of the chance to get cheap products for sellers is studied. We conclude on the
importance on institutions that are different from pure market interactions for the apparition of niches that are coherent with the observation we led on the market. The paper is organised in three parts: a description of the Fresh Fruits and Vegetables (FFV) wholesale market of Marseille and of interactions that induce merchant exchanges, a description of the model that was build to explore the impact of heterogeneous motivations, eventually results and a discussion of these results.

7.2 Modelling loyalty in markets

The classical economic approach focuses on a global signal to explain interaction: price. If one is interested in understanding patterns of behaviour that emerge in actual market, it is however important to realize that agents, most of the time, have no access to a global view that enables them to judge in real time if the proposed price is relevant. Hence learning processes, for individuals and at the system level, are still to be understood. Some recent economics trends (experimental economics and agent-based simulation) give new insights on interaction dynamics, by focusing on the study of interactions and negotiations and the importance of networks that enable a better circulation of knowledge (Vriend 2004). It is for example clear that the way the institution works has an impact: the shape of interactions networks (Burt 1992) or the existence of a community-based imitation or valuation of individuals has an impact on price dynamics (Hassoun 2004). In agent-based models, it has been shown for example that the speed of attaining the equilibrium depends on the information that is used (Rouchier and Robin 2006) or that the pool of buyers who are able to participate in the market is different when auction or bilateral bargaining is used to organize interaction (Moulet and Kirman 2008).

An aspect of the market that is stressed in our research is the fact that people tend to have regular relations with each other. This is an observation that is quite regular in
bilateral bargainning and opened the way to the construction of many models. Usually, the loyalty that emerges is due to learning for agents, who discover which interaction gives them the highest profit and choose to select those agents that enable it. In this case, the apparition of loyalty is shown to appear for certain values of learning parameters (Weisbuch, Kirman and Herreiner 2000). If buyers can also learn which prices to accept and sellers which prices to offer, the apparition of loyalty is parallel to price dispersion (Kirman and Vriend 2001). In some cases loyalty is not the main focus, but is the first step for agents to stabilize on some negotiation patterns, which can be compared to recorded micro-behaviour on the real market (Moulet and Rouchier 2007).

In these cases, the apparition of loyalty is always due to the attraction to highest profit. However, other interpretations can be given to loyalty in a market: it can be a sign of different motivations: the pleasure of interacting with well-known persons rather than strangers, moral norms, or an anticipation of the risk that searching for low price makes you come late and have no good left. In the paper we don’t discuss the reasons why agents choose an attitude or another, and there is no evolution of this attitude for the buyers. We will consider how these two ways of acting can cohabit, and see them as having a “function” on a market. The only learning that takes place in the market is the one of sellers, and we consider that they organise their supply thanks to step-by-step and averaging. Both methods are assumed to be usual learning in agent-based simulation although they are not the most usual in economic simulations (Weisbuch et al. 2000, Brenner 2006). Our evaluation of global results is based on economic issues, not from a price perspective but considering buyers’ satisfaction and global wastes, which seems quite suitable when dealing with food supply chains. This research follows a previous work on the influence of different rationality and information treatment on market dynamics, with rather close problematics (Rouchier et al. 2001).
7.3 Marseilles’ wholesale FFV market

The fresh fruits and vegetables (FFV) market of Marseille is the original focus of our interest. This market is one of the central nodes for the supply of Marseille and the region in terms of fresh products. The other important network that distributes FFV are the supermarket chains, which developed independently. Since the 70’s, this market has been seriously professionalized and has been established as a “Marché d’intérêt national” (MIN), National Interest Market (NIM). The market is for professionals only, who have to be registered as a supplier, a wholesale seller, a retailer or a restaurant owner (actors are referred to as he, since a huge majority of them are male). Observations and interviews were led on that markets, so that to identify the mechanism of price formation by the wholesale sellers and to evaluate the influence of both their suppliers (importers and producers) and their clients (retailers). This market is a professionals market. Contrary to consumers, professionals are deeply dependent of the prices and quality of goods they purchase, on which the survival of their business relies. Hence, it is quite logical to represent them as agents who look for information in a quite extensive way. It has been shown that this is less clear for consumers market where misinformation is so high that it is difficult to have it match with theoretical market. Since the justification for the existence of a formalised market in one place, for politics, is to attain a better spread of information and hence more fairness, this information issue is important.

The Arnavaux market takes place every morning apart from Sundays, in the suburb of Marseille, from 3:30 until about 9:00. Sellers are localised in two areas and are designated as producers and wholesale sellers. In the main area, there are big shops with display rooms and storage rooms, where the wholesale sellers wait for their clients. They work there all day long, have many employees to manage stock and orders, buy products in huge quan-
tities from some other professionals (their suppliers who can distribute local goods or import them). A second part is an open space protected only from the rain, where local producers come and display their own production, which they bring everyday in their truck: their presence depends on the season, and they are not very numerous in winter. Goods are purchased by wholesale sellers on an everyday basis, and they try to keep to the needs they anticipate from their former sells. They have more or less the same opportunities to get supply and prices are quite homogenous for incoming goods. The quantities depend on the arrival of boats and on the weather. With some products, the variations can be very important and generate volatility in prices (tomatoes, strawberries or zucchinis); whereas others are more stable and necessitate less strategic search for best prices. The volatility of prices is due to storage costs and to the fact that goods are perishable and have to be sold quickly: wholesale sellers reduce prices, sometimes drastically, when they want to get rid of the products. The heterogeneity of prices is hence mainly due to the co-existence of different qualities and ages of goods.

Most retailers we have interviewed come everyday to get their supply, with a list in their hand. They first go to the local producers’ area, where goods are fresher and they discover the day prices for locally grown goods. They then go and see wholesale sellers to complete their basket. To be able to evaluate prices and quality when they have to bargain, retailers have three main sources of information. First, there exists a public information sheet that gives an average price for each type of product for the previous day. The information is gathered by a man who comes on the market at about 11 and asks the wholesale seller about their average prices. The set of prices is then published for the next day. Apparently, on the Marseille market, this set of data is not really trusted because the man himself is not appreciated most retailers take into account the average prices from other markets in the Region. Another way to grab information is to interact with wholesale sellers - asking for the prices and choosing af-
ter a moment. Eventually, some groups of retailers can be informally organised so that to meet and share/exchange information. Most of the time, retailers who have this practice are known for it and wholesale sellers who do not appreciate collusion give them approximate data. The gathering of information can be very time-consuming and only retailers who have employees to install the shop can afford to stay a few hours on the market.

In the Arnavaux market, the relation between supply and demand is quite variable, and hence the negotiation power of both side of trade is changing regularly. From the suppliers point of view: some days they are glad because there is little food and they can make high prices; they fell much more insecure when there is too much: they have too much to sell at too low price, they will loose money if they have not anticipated the situation.

In the last case, they really need faithful retailers. But a retailer can be faithful if one has not been too aggressive in setting too high prices on a day with little supply, or if one has made a nice credit without asking for a fee.

From the retailer’s point of view, it is good to know that the price offered is reasonable without going around the whole market to compare. It can also be useful to have some predictions for the evolution of prices and be able to order some goods that will be kept. The days when only few products get to the market can indeed be of concern for retailers who need to get their usual supply. However, it is clear that agents are still in a context of competition and have to check regularly if the deal they have is good or not. There is a tension between staying in a familiar relation and putting pressure on the seller and ask for the advantages they wish (Hirschman 1970).

The relations are important for retailers for two reasons. First they get pressured by their own clients: the idea of continuity is fundamental for retailers who have to sell similar products all the time during the season; the quality aspect is also taken into account, and they have to trust a wholesale seller since quality can be judged only after a day or two. Second, they need good prices, and also short-term credit. For wholesale sellers, good rela-
tions are obviously important since they are a chance of selling goods. Even if a retailer does not buy goods one day, the fact that he comes in, talks about product or about the day market is very appreciated. This means that he will come back and might buy some other day; it also shows a form of respect which is very important to exhibit in this male context. When a retailer is well known, he usually gets the best price-quality ratio. Buying large quantities is also a way to get reduced prices. He can also get advises about purchases: wholesale sellers get permanent information about future supply and can help their retailers to organise their stock to avoid shortages or price increases. This last element is not represented in the model at all, whereas the reduction of prices are sketched. Two patterns of behaviour can be witnessed among the retailers: either they are mainly loyal to one wholesale seller or they are behaving in a market logic, comparing all prices before choosing. These characteristics have been observed and are consistent with other types of information on real markets, like the ones gathered on a fish market and analyzed in agent-based models by Alan Kirman (Weisbuch et al. 2000, Kirman 2001). In the domain of fruits and vegetables exchanges, these two behavioural patterns can also be observed in interactions between wholesale sellers and their suppliers (Brousseau and Codron 1998).

Among all the observed phenomena, we have reduced our model to represent only a small part of the market activities, focussing only on the practices of retailers and wholesale sellers. The number of products that are considered is limited and available in all wholesale sellers’ shops. Local producers activities are ignored; relations to suppliers are evocated as exogenous data giving supply probabilities, identical for all wholesale sellers. The reservation prices of wholesale sellers (minimum price to sell) are here exogenous. In reality they are due to the more general situation along supply chains, and are nowadays strongly influenced by supermarkets’ policy. There is no element either about the retailers activity in the city. We consider that accurate information on individual whole-
sale sellers’ stocks and prices is available to retailers if they take time to gather it. In the interactions between wholesale sellers and retailers, we only consider merchant exchanges and don’t integrate credit facilities or information circulation. The logic of retailers are of two sorts: either they try and get as many goods as possible with a limited number of wholesale sellers, being first loyal to their main colleague; or they go and fetch the cheapest products they can, according to the information they gather.

Hence we can summarize the hypotheses:

• In the market we consider, there is no centralized mechanism to aggregate information about the prices at which transactions are concluded.

• The information about the price of transaction is private. No explicit information is shared among buyers nor sellers.

• Good is perishable, so buyers have to come regularly on the market, sellers have a high incentive to sell the good, which looses N % of its price everyday and is thrown after 3 days.

• The supply is made by one source defined by: the probability to get the desired good, the distribution of prices. The wholesale sellers reduce the price of a good when days pass by. Sellers learn to choose the supply.

• Information gathering activity is an individual activity. Buying activity and information gathering activity are separated.

We are interested in testing the impact of the ratio of loyal and opportunistic buyers, with different distribution of availability to goods and prices. In this model, only Sellers learn and we test several type of learning. Our observation of the market is global and linked to an idea of ‘good functioning’, based on two elements: the satisfaction of retailers in terms of supply, the quantity of garbage that is produced on that market.
7.4 Model, simulation and observed data

The market contains 10 sellers and 100 buyers. There are 10 different goods that are defined by their price and their age. Goods lose all their value over three days, and are then thrown away. Each day, buyers come with a list of five goods they desire, one unit of good per day. Sellers prepare the supply at the beginning of the day, and each good they buy is associated to a price. There are two types of buyers: loyal and opportunistic. The market day is divided in 3 periods:

1. Loyal agents go to see their favourite seller, opportunistic agents get information.

2. Loyal agents who are not satisfied look for information and opportunistic agents get the cheapest product they can.

3. All agents who are not satisfied get some goods (using the same information they had at second step). Then all agents evaluate the sellers they met.

**Negotiations.** They are very limited. Buyers ask for a good or a bunch of goods. Sellers answer by giving the list of available products and the price (the list can be empty). Buyers can only accept.

**Information.** Buyers get information about the quality and prices that can be found at each seller’s shop and decide who to visit according to this information.

**Good.** A good is defined by its type (one of the ten products), its age and its price.

**Buyer.** is defined by its need, its type and its favorite seller if it is a loyal buyer. The behaviour of a seller is automatic: it decides on the seller to visit, either by going to the favorite one or by selecting the seller with the cheapest basket or the fullest one. The order in which buyers get in the system is randomly arranged at every time-step.

**Seller.** is defined by its stock (list of goods), and its supply. It is able to detect a Buyer who is regular (who
came at least five times out of ten days) and provides it with the freshest good. The way it updates its supply follows four learning algorithms:

- Step-by-step learning, with an increase of 2 when goods are lacking and a decrease of 1 when garbage is produced

- Average over 5 steps, the supply asked being the average quantity of demand over 5 time-steps

- Average over 10 steps, the supply asked being the average quantity of demand over 10 time-steps

Simulations are run for 100 time-steps. A simulation is defined by:

- the number of loyal buyers (values being here 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100)

- the probability of getting cheap goods for a seller (0.1, 0.2, 0.5, 0.8, 1)

- the price difference among sellers in percentage (0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1)

- the learning of sellers (5 step memory, 10 step memory, step-by-step).

We hence use two variables to represent the heterogeneity of prices among agents, one variable which is our key variable to see the role of loyal agents in the market, and one variable to make sure the results are not dependent to learning. The data that we are mainly interested in gathering is the garbage (number of thrown units), which is a sign of bad anticipation for supply. We can also observe the lack of supply for agents, age of average good that is sold.
7.5 Dynamic properties and discussion

7.5.1 General remarks

During a simulation, Retailers go and see WholesaleSeller everyday. On the first period, only loyal Retailers get into shops, then on the second period only opportunistic ones get in, and eventually on the third period all Retailers which have not fulfilled their needs do go to shops. Loyal agents spend on average more money than opportunistic agents when they are on the market, since they look for availability, not for cheap prices. Loyal agents also usually leave the market earlier and have led much less transactions. Those results are true when both types of agents coexist, but also when there is only one type of each. This is a logical conclusion from the model, since at each period opportunistic agents can go and see up to five different WholesaleSellers with an average of about 3. Even if, in this paper, we did not interpret loyalty as a solution to reduce transaction costs, it is important (to keep up with observed facts) that our system produce a coherent setting where much more energy is use in negotiation by the opportunistic Retailers.

Along the time the quantity of goods that each Seller acquires converges to a value that does not change too much after the 40th day, which can be considered as the moment when the system equilibrates. In the dynamics, opportunistic Retailers have a disadvantage, in that they always get served after the loyal ones and should have more problems to have goods. However, with the adaptation of the supply of Sellers, even if at the beginning of the simulation there is a regular lack of goods, all Retailers have a chance to get goods after a few periods. In non extreme simulations\(^2\), for example with a variation of price of 40 and an ability to get supply of 80, Regular Buyers can acquire 90% of the required goods.

\(^2\)Extreme simulations will be treated in the next subsection, they concern the cases when there is a small heterogeneity among Sellers and where the attitude of Buyers has no big influence
Loyal Buyers can get 87%. They always acquire equivalent quantities or slightly less, but not significantly less. It thus seems that the time organisation of the system does not put such a big bias on the access to goods, although it can seem to do so at first estimation.

In a first version of the model, we had set the reaction of the Sellers to the presence of a regular Buyer (asking for at least 5 goods every two steps, which means half of its demand) to be either to provide cheap goods or to provide freshest goods. With the simulations where they would provide cheap goods to regular Buyers, the price paid by Loyal Buyers is less than the price paid by Opportunistic Buyers, which is in contradiction with many observations on perishable goods markets (Kirman, comm. pers.). In the Arnavaux market, the interviewed sellers said they tend to give fresh goods to agents who are regular and loyal. Hence, we decided to choose only the alternative with Sellers providing the freshest goods to regular Buyers so that to fit actors’ declaration and researchers’ observations. This elements has an impact on the age of products acquired by Opportunistic Buyers. Since fresh goods are given more often to Loyal Buyers, and since Opportunistic Buyers look for cheap prices, with older goods getting cheaper, the Opportunistic agents acquire goods that are on average older (0.3 days) than the ones acquired by Loyal Buyers (0.15 days).

7.5.2 Anticipation of needed supply

The main result of this research is the fact that the presence of Opportunistic Buyers, in most settings, increases the quantity of garbage. The main reason is that the Opportunistic Buyers make requests that are not regularly addressed to the same Seller, and hence the information that Sellers get to organise their supply is not accurate to project needs in the future. This rather intuitive result stands only for part of the simulations that are performed, since it depends also on the heterogenity of prices and availability of cheap supply. Watching the figure 7.1 one can see that a high number of Loyal Buyers enables
Sellers to organise very well their supply, with an average of 23 thrown units over 100 time-steps, going from 18 to 31, for any values of parameters. On the opposite, the number of garbage for Opportunistic Sellers can be very different depending on the choice of parameters and this is what we explore here. We will call these situations extreme cases, since they represent the limits of our parameter space.

The first situation where the number of Loyal Buyers does not change the ability of Sellers to anticipate is the case when the price difference between goods is zero. In figure 7.2 this result is visible. The result is straightforward, considering the choice algorithm for Buyers: since Opportunistic Buyers choose the Seller only on the basis of prices, if Sellers are homogeneous, they choose randomly and hence, the information that Sellers get is the probability of being randomly picked, and they adapt to this.

This result also stands for the cases when the probability of supply for the cheap good is 1. In this case, there is no discrimination for Buyers either, since all Sellers offer the same good, the cheapest one. As can be seen in figure 7.3, whatever the rationality, Sellers can get an accurate information about the demand they get. Again, the random situation allows them to learn efficiently with all algorithms that are used here. As can be seen on the same figure 7.3, when the supply probability is low (0.20), garbage is also less important, since Sellers are close to homogeneity, most of their offer being at the expensive price.

If one removes all values where the heterogeneity is reduced among sellers, then the influence of loyalty gets very clear in our system, as figure 7.4 shows, with values of garbage for different simulations and average values given as well.

7.5.3 Influence of learning

The learning of Sellers can be of three types. The impact of each learning is different in terms of global dynamics of
Figure 7.1: Total quantity of garbage for a simulation. For all simulations (all possible values of difference of price, limits to availability, leaning of Sellers) the quantity of garbage produced, the more Opportunistic Buyers in the market, the more garbage. It is however possible to see that in some cases, event with no Loyal Buyers in the market, there is little garbage. (FIG. 7.1).
Figure 7.2: Total quantity of garbage for a simulation in the case when there is no difference of price among Sellers for fresh products. It is clear that the number of Loyal Buyers has a very small impact, and even that a having only Opportunistic Buyers can reduce the quantity of garbage. (FIG. 7.2).
Figure 7.3: Total quantity of garbage for a simulation for all values of difference of price, number of Loyal agents and learning of Sellers. The case when the probability to get cheap goods is 1, the quantity of garbage is equivalent to the situations where there are only Loyal Buyers. (FIG. 7.3).
Figure 7.4: Total quantity of garbage in situation where Sellers are heterogeneous enough (difference of price is higher than 10, availability of cheap goods is between 40 and 80). The influence of the presence of Loyal agents in the system is then really clear (FIG. 7.4).
garbage, but the difference is not very significant, except when there are only few Loyal Buyers. The figure 7.5 is based on simulation with heterogeneity, and hence when the lack of Loyal Buyers make it difficult for Sellers to learn. The fact that the step-by-step learning is the best in most cases is quite easy to explain, considering the dynamics. In the system, the quantity of cheap good, the difference of prices and the request for supply that each Seller makes, based on its ideal supply and its remaining goods, all these factors influence the quantity of cheap goods that each Seller can offer, and hence the relative attractiveness of each Seller for Opportunistic Buyers. A learning that is based on 5 or 10 time-step average can hardly approximate the demand that a Seller will face in such a varying environment on a daily basis. This explains why the three learning give closer results when the number of Loyal Buyers increase. In most situation, step-by-step learning gives the lowest quantity of garbage. The reason can be found in the fact that the system includes a lot of randomness, within a range that is usually not so large. Hence, in the case when there are no Loyal Buyers, 5 step-average learning gives the best results. The explanation is not sure yet, but one assumption is that it is due to the permanence of This can be understood by the fact that in this case, all agents are only interested in cheap prices. When a Seller who is relatively expensive at one time-step, its goods stay and are also still expensive at the next time-step (we are here facing cases where heterogeneity in prices is such that even old expensive goods are slightly more expensive than cheap fresh goods). Hence the relative unattractiveness of the Seller will last for three time-steps and the adjustment of the Seller to the demand will be based of 5 time-steps, which is the right span. On the opposite, a 10 time-step learning in this case cannot take into account the rapid change of opportunity for a Seller who potentially gets cheap goods, then expensive one and can change its attractiveness very fast. In this last case, the goods are lacking and garbage is high. It is not easy to explain why then the step-by-step learning is not as
good as 5 step learning to avoid garbage, but it is interesting that Buyers can get the quantity they ask for more easily in this last case. It is one of the only cases when there is not an exact correlation between the bad supply and high garbage. However, our system was not conceive to treat in an extensive way of the case of Opportunistic Buyers, which are usually modelled in a much more sophisticated fashion, with search algorithms that enables them to create to a high efficiency of the market.

7.6 Conclusion

The main dynamical feature of the model we built gives an indication of the role of loyal buyers in a market, in that they are the support for an anticipation of demand for sellers. This result is rather coherent with what was found out in the field study, since on the MIN market, stable relations are recognised as important on both sides. To test how the local motivations could have an impact on global results, we hence built a multi-agent system in which to perform simulations. The conclusion that we can draw is of several dimensions: first, one can recognise that the individual behaviours do have an impact on the performance of individuals and on the functioning of the market as a whole. The presence of too many selfish agents pushes to a very important destruction of products. Maybe one can then understand why the wholesale seller we interviewed declared that it is a very important to push retailers to loyalty. And one can see how the degree of stability of the environment (variations of prices and of supply) can have an impact on the good functioning, as well as on a emerging heterogeneity.

Following this work a few other steps need to be reached. First, it is necessary to study the relation dynamics among agents, and even transform the rules a bit. It would indeed be interesting to conduct the same experiments with loyal Retailers who would be able to evaluate their relation to their regular, and potentially turn out to be selfish for a moment if they are not satisfied looking
Figure 7.5: Average quantity of garbage for all simulations in a heterogeneous setting. The main difference is noticeable when there are only few Loyal Buyers. Especially in that case, averaging demand over 10 time-steps is not a relevant learning method. (FIG. 7.5).
for a new regular to settle with. On the other side, one could consider that the selfish agents could at some point decide to stay with one agent who could fulfil its needs in most of the case.

This paper represents an attempt to link field observations to a formal (computer) model. We try to take inspiration in directly gathered data, building models from observations, so that to identify the logic of actors, often based on few data, with little time to compute, and hence inducing choices that are closer to “local satisfying” than “exhaustive optimising” ones. Our relation to the field study is related to the ‘companion modelling approach developed by François Bousquet and others (Barreteau and Bousquet 2000), although we are not dealing with public good issues. This field implication also makes it harder to stick to a very strict theoretical context, but the modelling process offers an intermediate step between classical representation and pure description. Our choice is indeed to try to express in a formal way the motivational aspects of an everyday life activity which is far from one shot meetings, but also from monetary preferences, since individuals sometimes value other dimensions of their experience as it is well-known from old observations. Here we did not study the market as a price setting device, but as a supply organisation device. Prices are close to being fixed by outside constraints. Even if we study the impact of the ratio of loyal vs opportunistic agents, the aim is not to spot the ’best’ ratio. We just wanted to show that there might a good reason why the equilibrium of number of buyers of both sides is encouraged by sellers.

First, we are more interested in producing setting that fits qualitative estimation of the system dynamics, than one that would fit to quantitative data. One reason for this choice is practical: we are in the process of gathering data, and it is not clear how exhaustive the treatment can be. People don’t necessarily answer honestly facing a question about acquaintances and credit facilities (in France money issues are often taboo), a lot of exchanges take place via unofficial networks (Tarrius 2002),
are voluntarily hidden, or simply taking place by telephone or as routines that are difficult to register exhaustively. The other reason is that we want to interact in a reciprocal way with our informers, and hence produce qualitatively coherent data that they can interpret as easily as possible. Artificial worlds being recognised as a good way to attain this interaction. Through that mean we wish to capture the actual mechanisms that are used by merchants and potentially be able to provide to the actors some insights on their practices. Indeed, along the modelling process, the results have been commented by our main contact on the market, which helped us to the refine the model.


Simulations Informatiques in *Les Systèmes Agro-Alimentaires Localisés (Syal)*, CIRAD.


