The effect of buyers and sellers on fish market prices[#]

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Abstract

This paper extends the traditional hedonic price specification to take into account the unobserved heterogeneity of sellers, buyers and seller-buyer matches. The specification is estimated using econometric techniques for non-nested panel data models on a dataset of nearly 15 million transactions occurring in French wholesale fish markets over the 2002-2007 period. Results show that unobserved heterogeneity plays a significant role in price setting. For some species, its inclusion in price regressions changes the coefficients of quality-related fish characteristics. Fish characteristics are the main factor explaining price variations for many species, but time and buyer effects also play a significant role.

Keywords: fish, commodity price, unobserved heterogeneity, variance analysis, panel data

JEL Classification: L11, Q22

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1. Introduction

Hedonic price regressions introduced by the seminal paper of Rosen (1974) have become a widely used approach to study how prices of commodity goods are affected by quality attributes. Each good is characterized by a set of observable attributes and, when there is perfect competition, the price of a given good is fixed at a unique value on the market according to supply and demand. The marginal price of every attribute at equilibrium is evaluated from the regression of the unit price on the whole set of attributes.

There are several reasons why this framework may not be valid in practice. First, some quality attributes are not observed and they vary among commodity goods with the same observable attributes (Bajari and Benkard, 2005). Second, the market is imperfect due to rationing and/or spatial and informational frictions (Sorensen, 2000). Because of that, transaction prices will be related to the characteristics of agents influencing their moving costs and information. Moreover, some goods will be sold at different prices by producers with different willingness to sell, or will be bought at different prices by consumers with different willingness to pay.

In this paper, we argue that it is possible to quantify the way imperfections and agents' heterogeneity influence market prices by studying variations of prices with the characteristics of sellers and buyers, once the attributes of goods have been taken into account. As some relevant characteristics of agents are usually missing from the data, seller and buyer unobservable characteristics should be taken into account. The pairing between sellers and buyers (i.e. matches) may also matter since the information on the unobserved quality of goods sold by some sellers may be known only by some buyers. The goal of our paper is to quantify the influence of agents and matches on prices in agricultural economics by estimating hedonic price specifications involving seller, buyer and seller-buyer unobserved heterogeneity terms.

Our application relies on a unique exhaustive dataset of around 15 million transactions on the French wholesale fish auction market over the 2002-2007 period. Our data track sellers and buyers across transactions and contain repeated transactions involving the same economic agents. These specificities allow the separate identification of the different sources of unobserved heterogeneity. Provided that similar data are available, our work can be replicated to study the prices of any product whether it is raw food, transformed food or even a manufactured good.

Estimations are conducted using econometric techniques for non-nested panel data models that have been proposed in labor economics. Since the seminal paper by Abowd, Kramarz and Margolis (1999), a literature has developed incorporating the unobserved heterogeneity of firms and workers in wage regressions through the use of two series of fixed effects. This approach has been expanded to take into account specific effects for pairs of firms and workers (Woodcock, 2008, 2015; Sørensen and Vejlin, 2013). In our paper, we use a similar approach for fish prices per kilogram with a specification incorporating fish characteristics, time fixed effects, seller fixed effects, buyer fixed effects and seller-buyer match effects. Identification is guaranteed by the tracking across time of sellers and buyers.

Our work complements the literature on hedonic price regressions that takes into account unobserved seller heterogeneity using store fixed effects when retail prices are studied (Lach, 2002). The most significant applications on specific food products mostly concern wine (Nerlove, 1995; Combris, Lecocq and Visser, 1997; Ashenfelter, 2008), cereals (Stanley and Tschirhart, 1991) and fish. For applications on fish, hedonic price regressions have been used to study prices of fish sold at wholesale auction (McConnell and Strand, 2000; Kristofersson and Rickertsen, 2004), to analyze retail prices in shops to assess the importance of packaging, brand or eco-labelling (Roheim, Gardiner and Asche, 2007; Roheim, Asche and Insignares, 2011), and to test whether there are significant price variations across local markets (Gobillon and Wolff, 2016).[1]

The heterogeneity of sellers has been taken into account through the type of fishing gear for ships selling directly on the wholesale market since it can affect the quantity of caught fish, quality and profit (Kristofersson and Rickertsen, 2009; Asche and Guillen, 2012), but also through fixed effects for retailers selling on the downstream fish market (Asche *et al.*, 2015). The heterogeneity of buyers is less often considered and has been introduced through their distance to market (Kristofersson and Rickertsen, 2007) and fixed effects for plants where fish is delivered (Asche, Chen and Smith, 2015). The heterogeneity in purchase prices across wholesale buyers may also reflect differences in resale prices transmitted across the supply chain (Guillotreau, Legrel and Simioni, 2005). The paper closest to ours is Lee (2014) who considers simultaneously seller and buyer fixed effects in a hedonic specification used to study cod prices. In our work, we additionally consider how specific pairings of sellers and buyers may influence prices.

We investigate two issues for a large number of fish and crustacean species by estimating hedonic price specifications from data on transactions occurring on all French fish ex-vessel markets. First, we assess to what extent taking into account the unobserved heterogeneity of sellers, buyers, and seller-buyer matches changes the estimated effects of fish characteristics on prices. Indeed, some agents are willing to sell or buy for higher prices and they may be more likely to be involved in transactions of fish with specific characteristics on a segment of the market. In that case, we want to distinguish the average market valuation of fish characteristics from the sorting of agents when studying fish prices. To investigate this issue, we compare the estimates of hedonic price specifications that include or not unobserved heterogeneity terms.

[1] Controlled experiments have also been used to assess consumers' willingness to pay for specific fish attributes such as color (Alfnes *et al.*, 2006).

Second, we quantify the role of unobserved heterogeneity terms in explaining variations in fish prices. This is done by assessing their additional explanatory power when added to specifications and by conducting a variance analysis based on estimated hedonic specifications that include all the unobserved heterogeneity terms. We evaluate whether unobserved heterogeneity significantly contributes to variations in fish prices compared to observable fish characteristics.

The rest of the paper is organized as follows. Section 2 describes the empirical strategy used to quantify the importance of fish characteristics, time, seller, buyer and match effects in explaining variations in fish prices. Section 3 presents our dataset of fish transactions along with descriptive statistics. Section 4 comments our results and Section 5 concludes.

2. Empirical strategy

In this section, we explain how unobserved heterogeneity can be incorporated in hedonic price regressions when panel data on fish transactions are available, and sellers as well as buyers can be tracked across time. We also explain how the role of factors in explaining fish price variations can be quantified.

For a given fish species, we denote by P_i the log price of a transaction i. We assume that it depends on the characteristics of the fish lot X_i composed of dummy variables related to size, presentation and quality as these attributes are usually considered to influence fish demand and thus prices (see for instance McConnell and Strand, 2000). The standard hedonic specification is given by:

$$P_i = X_i\beta + \vartheta_{t(i)} + \epsilon_i \tag{1}$$

where β is a vector of parameters, ϑ_t is a time fixed effect, $t(i)$ is the month at which the transaction occurs, and ϵ_i is a random error term.[2] This specification is usually estimated with Ordinary Least Squares.

There are several reasons why price variations may remain once observable fish characteristics and time of sale have been taken into account. First, there can be differences in unobserved fish attributes valued by customers across fish lots. These differences can come not only from variations in the fishing gear used by vessels,[3] but also from differences in skipper skills that may affect how well fish is captured and chilled or iced onboard. Indeed, the literature has shown in some specific contexts that skippers have an influence on production efficiency (Viswanath *et al*., 2001; Pascoe and Coglan, 2002; Wolff, Squires and Guillotreau, 2013).

[2] Note that for simplicity, the coefficients of fish characteristics are assumed to be constant over time. This assumption may be violated in practice since the preferences of customers and the availability of fish with specific characteristics may well vary over time. In that case, the estimated time fixed effects pick up the estimated time variations of the effects of fish characteristics. This should be kept in mind when interpreting the results.

[3] The literature uses the term "vessel" to refer to ships landing and selling fish on the wholesale fish market.

Second, there are several kinds of imperfections on fish markets. Some rationing can occur since fish catches vary across places depending for instance on the weather conditions of the day and since there are no stocks. In that context, some buyers such as restaurant providers want to be sure to obtain fish with specific characteristics and will be ready to pay high prices. Moreover, there are spatial and informational frictions. Vessels are limited in the markets where they land their catches by the place where they fish because of moving costs. Buyers' location matters since it determines their prospection and transport costs, making them more likely to purchase on a given spatial segment of the market. Moreover, some buyers know better how to get information on the daily fish available.

All these imperfections can make similar fish lots being sold at different prices, especially when sellers and buyers are heterogeneous. The heterogeneity of sellers, as well as all the unobserved quality dimensions of products due to vessel and skipper characteristics, can be captured with seller unobserved effects denoted γ_j. The heterogeneity of buyers can be captured with buyer unobserved effects denoted δ_k. The use of unspecified effects avoids the risk of being non-exhaustive with characteristics of agents and products introduced in regressions. As we will see below when describing the data, buyers cannot be tracked across fish markets.[4] Hence, unspecified buyer effects cannot be identified separately from market effects. The specification becomes:

$$P_i = X_i\beta + \vartheta_{t(i)} + \gamma_{j(i)} + \delta_{k(i)} + \epsilon_i \tag{2}$$

where $j(i)$ is the seller involved in transaction i and $k(i)$ is the buyer. We treat the buyer- and seller-specific components as fixed effects because they may be correlated with the covariates X_i. For instance, vessels fishing very close to coasts and landing their catches daily are expected to sell small quantities of high-quality fresh fish, whereas large vessels operating away from coasts sell fish which has been chilled or frozen in large quantities after several weeks at sea. These two types of vessels may not sell fish with same unobserved quality, and the effects of observable fish characteristics may capture that of unobserved quality. In the same way, fish traders supplying restaurants will seek to buy high-quality fish, while traders supplying supermarkets will purchase a broader range of fish species at lower prices. The willingness to pay is unobserved and can be correlated with the measured fish quality which is introduced in the set of explanatory variables.

Specification (2) is a panel data model with two large series of non-nested fixed effects, one for sellers and one for buyers. This type of model has been studied in the labor literature since the seminal paper by Abowd, Kramarz and Margolis (1999) who estimate a wage equation with both worker and firm fixed effects. In our context, identification of fixed effects is possible only within groups of well-interconnected sellers and buyers (see Abowd, Creecy and Kramarz, 2002, for more

[4] In our data, we only have the license codes of accounts used by buyers to purchase fish. These license codes are market-specific and can thus be tracked only within markets.

details). Interconnection within a group is ensured because vessels sell fish to several buyers within the group and buyers purchase from several sellers during the period covered by the data. Groups are mutually exclusive as no buyer in a group purchases fish from a vessel in another group. We only study the main group of well-interconnected vessels and buyers which includes nearly all transactions for most species in our data. As there are large numbers of seller and buyer fixed effects in the model, estimations are performed in two steps, as explained in Appendix A.

The specific pairing of sellers and buyers can also matter. This might occur because some buyers, such as primary processors supplying restaurants on a regular basis and retailers supplying their own shops, may make higher bids on specific weekdays (Friday for instance) when specific vessels are selling their catches on the market. On-site buyers may have better information on the high quality of fish lots from specific vessels and may be ready to pay higher prices at auctions than remote internet bidders.[5] In our application, fish lots are sold at auction. As this precludes direct sales from sellers to buyers, we do not expect loyalty relationship to play a significant role in matches as in a pairwise fish market (Kirman and Vriend, 2001; Cirillo, Tedeschi and Gallegati, 2012). More generally, match effects correspond to the price premiums that some buyers agree to pay to some specific sellers.

We introduce in equation (2) the effect of a specific association between a seller j and a buyer k (the match effect), denoted by θ_{jk}, as specific matches can influence fish prices. The resulting model can be decomposed into the two following equations:

$$P_i = X_i\beta + \vartheta_{t(i)} + \mu_{j(i)k(i)} + \epsilon_i \tag{3a}$$

$$\mu_{jk} = \gamma_j + \delta_k + \theta_{jk} \tag{3b}$$

In equation (3a), μ_{jk} is a seller-buyer fixed effect capturing all the unobserved heterogeneity terms.[6] This fixed effect is decomposed in equation (3b) into the seller fixed effect, the buyer fixed effect and the match effect. The identification of this model is extensively discussed in Woodcock (2008, 2015). The accuracy with which a term μ_{jk} is estimated increases with the number of transactions between seller j and buyer k. For γ_j, δ_k and θ_{jk} to be separately identified, match effects must be considered as orthogonal to seller and buyer fixed effects. As before, sellers and buyers must be inter-connected, so we restrict the estimations to the main group of well-interconnected sellers and buyers. The estimation procedure is again detailed in Appendix A. Standard errors are clustered by group defined according to size, presentation and category to avoid biases due to group shocks (see Moulton, 1990; Asche *et al.*, 2015).

[5] Indeed, they can acquire information by talking to vessel skippers as well as by observing the fish from different angles before the sale occurs.

[6] It would be tempting to simply introduce the match effect in equation (2) as a random effect and take it into account using standard panel estimation techniques. However, this approach is less general than ours since it does not allow for a correlation between fish characteristics and match effects. Our approach is robust to that issue.

Our most general specification given by (3a) and (3b) is used to perform a variance analysis of fish prices. The role of fish characteristics, time, sellers, buyers and matches in explaining variations in fish prices is measured by the ratio between the variance of their effect and the variance of prices. For instance, denote by $\hat{\beta}$ the estimated coefficients of fish characteristics and by $V(\cdot)$ the operator giving the variance. The importance of fish characteristics is measured by the ratio $V\left(X_i\hat{\beta}\right)/V(P_i)$.

3. Description of the data

We now give some information on the French fish markets and our dataset on fish transactions. Over the 2002-2007 period, 230,000 tons of fish were landed and sold every year in France, for an average value of 658 million euros and an average price of 2.85 euros per kilogram (France Agrimer, 2012). The tonnage represents about 30% of total domestically produced seafood when frozen fish and aquaculture products are taken into account, but it represents only around 10% of domestic demand which mostly depends on imports. Fish is traded in markets between vessels and buyers, mainly at auctions in trading rooms or using a mobile electronic auction clock, but also increasingly by internet to involve remote bidders (see Guillotreau and Jiménez-Toribio, 2011, for more details).

In France, information on every transaction is collected by the national bureau of seafood products (France Agrimer). This information is then processed into a data system called RIC (Réseau Inter-Criées) and added to a unique dataset that we use in our empirical analysis. This dataset is exhaustive for all transactions on the domestic fresh fish market in France between January 2002 and December 2007. The data contain a small number of variables providing an accurate description of transactions.

We know the quantity purchased and the total value paid by the buyer, from which we deduce the price paid per kilogram. We have the usual detailed characteristics of fish involved in the transaction: species, size, presentation (whole, gutted, in pieces, etc.) and quality measured by freshness (given in descending order from extra to low). The month and year of transactions are recorded but the exact day is not available. We also know whether fish is traded in auction or directly sold to the buyer. Finally, the dataset includes two identifiers, for vessels and buyers respectively. The buyer identifier is a license code corresponding to an account specific to a local marketplace. A limitation of our data is that it is not possible to identify whether several accounts are owned by the same agent. To ease the exposition, we will refer to an account as a buyer, but it should be kept in mind that several accounts on one or several markets may correspond to a single buyer.

Overall, the dataset includes 18,197,738 observations over the 2002-2007 period. We restrict the sample to transactions sold at auctions for species involving more than 60,000 transactions. In line with our empirical strategy, we keep for each species the largest group of well inter-connected sellers and buyers and restrict our attention to species for which this group involves most transactions. More details on the selection of transactions are available in Appendix B. Our selection procedure leaves us with a sample of 14,564,758 transactions of fish and crustaceans belonging to 46 species. The main group of well inter-connected sellers and buyers involves more than 99.6% of transactions for 42 fish species, and the minimum proportion of transactions involved in the main group is 95.1%.

Contributions of species to total sales are reported in Table 1 which shows that trade is concentrated on a limited number of species. The two main species, sole and monkfish, represent 26.9% of total sale value. The first five species represent 44.2% of this value and the first ten species 66.7%. There is considerable heterogeneity in the average price per kilogram. The most expensive species is lobster, with a price per kilogram around 21 euros. There are several very cheap species, such as whiting or mackerel, with a price per kilogram ranging between 1.5 and 2.5 euros.

[Insert Table 1 here]

Table 2 sheds some light on the market structure. The numbers of buyers and sellers vary considerably across species. Among species which represent a significant share of total sale value, there are around 3,200 vessels selling to 3,000 buyers for sole, and 400 vessels selling to 1,000 buyers for Norway lobster (live). What matters in our empirical application is the degree of interconnection between them. It can be crudely assessed from the number of buyers per seller and the number of sellers per buyer. For all species in our sample, there is a very good inter-connection between sellers and buyers. For instance, for sole, each vessel sells fish to 43 buyers on average and each buyer purchases fish from 40 sellers on average. The two numbers exceed 12 for all species. The average number of buyers per seller is 23 and the average number of sellers per buyer is 25.

[Insert Table 2 here]

A match is defined as a seller-buyer pair involved in at least one transaction. The number of matches varies a great deal across species. Among species with a significant market share, there are 129,482 matches for sole and 25,437 for Norway lobster (live). The minimum for all species is 10,328 and the average is 44,231. The correlations between number of matches and numbers of sellers and buyers are 0.82 and 0.88, respectively. The estimation accuracy of match effects depends on the number of transactions per match. Figure 1 gives statistics on the number of transactions per match for every species. The first decile is 2 or above for all species except two (grey mullet and lobster). The median is quite high as it takes a value of 8 or above for all species. Finally, the ninth decile is above 30 for all species and reaches a maximum for sole at 144.

[Insert Figure 1 here]

4. Empirical results

4.1. Hedonic prices regressions

We now comment the results of hedonic price regressions estimated by Ordinary Least Squares for the two species which have by far the largest market shares, sole and monkfish. We begin the analysis by assessing to what extent fish characteristics can explain price variations from changes in R^2 when introducing successively in the specification time, size, presentation and quality dummy variables.

The changes in R^2 reported in Figure 2 show that, for sole, size matters the most, as the R^2 increases from 10.8% when time is introduced alone to 40.1% when size is added to the specification. Presentation and quality are only of secondary importance since the R^2 increases further to 48.1% when all the fish characteristics are considered. The story is different for monkfish as the R^2 is only 18.9% when both time and size are introduced, but it increases sharply to 52.3% when adding presentation, which makes this attribute the most important in explaining prices. Finally, the R^2 increases only marginally to 58.2% when also adding quality.

[Insert Figure 2 here]

Estimated coefficients of fish characteristics corresponding to equation 1 are reported for sole in Panel A of Table 3 and have the expected sign.[7] While small fish (sizes 4 and 5, and to a lesser extent size 3) is cheaper than large fish (size 1), medium-sized fish (size 2) is the most expensive. Medium-sized fish is 6.1% more expensive than large fish, but the smallest fish is 40.2% less expensive.[8] Results are consistent with medium-sized fish being the most valued. Presentation significantly influences price per kilogram. Low-quality fish (grade B) is 49.3% cheaper than extra-quality fish (grade E).[9] Gutted fish is 7.9% more expensive than whole fish because non-edible parts have been eliminated. Month-year effects are represented in Figure A1 of the Online Appendix. Overall, there is an upward trend over time. Prices also exhibit seasonality effects, fish being more expensive during summer holidays (July and August) and in December when demand is higher during the Christmas and New Year period.

[Insert Table 3]

We then estimate a specification corresponding to equation 2 where both seller and buyer fixed effects have been added. Results reported in column (2) of panel A show a significant improvement

[7] The quantity of fish purchased is excluded from the specification. Indeed, it is potentially endogenous since fish lot sizes may be influenced by the expected selling price. Still, we conducted a robustness check to assess whether adding the logarithm of fish quantity to our specification affects the results. Whereas this variable is found to have a significant negative effect, its inclusion has absolutely no effect on the magnitude of the coefficients of fish characteristics and does not improve the fit of the model. For instance, for sole, the R^2 increases only at the margin from 0.4814 to 0.4818 when adding fish quantity to the set of explanatory variables.

[8] These percentages are given by (exp(0.059)-1)*100 and (exp(-0.515)-1)*100, respectively. Other percentages in the text are computed in the same way.

[9] Note that there are significant differences in fish prices across quality grades whereas quality only explains a small share of price variations. This occurs because even if quality grade B has a large negative effect, the proportion of fish with that quality grade is small (2.4%).

of the fit, with an increase of the R^2 from 0.48 to 0.61 (+27%). This suggests some heterogeneity across vessels and buyers. Some coefficients of fish characteristics change when seller and buyer fixed effects are included in the model, but the results remain qualitatively similar. In particular, the price of gutted fish is now only 1.2% higher than that of whole fish (compared to 7.9% in column 1).

Finally, we consider a hedonic price specification with seller-buyer fixed effects corresponding to equation 3a. Results reported in column 3 show that the fit improves again, with the R^2 increasing from 0.61 to 0.66 (+8.2%). This increase may seem rather modest, but the contribution of match effects to explaining variations in fish prices is significant, accounting for 25.3% of the overall contribution of unobserved heterogeneity terms.[10] The introduction of seller-buyer fixed effects instead of seller and buyer fixed effects does not have much effect on the coefficients of fish characteristics. Also, the profile of time effects when all sources of unobserved heterogeneity are taken into account is nearly confounded with the one obtained without any source of unobserved heterogeneity.

Results obtained for monkfish are reported in Panel B and lead to quite similar overall conclusions. Ordinary Least Squares estimates show that prices are higher for fish which is larger, of better quality, or sold in pieces (column 1). As shown in Figure A2 of the Online Appendix, there is both an upward time trend and a seasonal effect, with fish being more expensive in December. Introducing seller and buyer fixed effects in a standard hedonic price regression increases the R^2 from 0.58 to 0.69 (column 2). Introducing seller-buyer fixed effects instead of seller and buyer fixed effects increases the R^2 to 0.73 (column 3). Hence, all sources of unobserved heterogeneity contribute to explaining price variations. Estimated coefficients of fish characteristics are influenced by the presence of unobserved heterogeneity. In particular, whereas gutted fish is 4.7% cheaper than whole fish when the specification does not contain any heterogeneity term, it is found to be 16.2% more expensive when seller and buyer fixed effects are added.

We estimate hedonic price regressions for every fish species to obtain systematic conclusions. The sign and level of significance of estimated coefficients for every species are summarized in Table 4.[11] We find that the price of small-size fish is lower for most species, but this is not true for squid, lobster and ling for which it is significantly higher. This can be explained by smaller fish being better valued on the market for these species because they correspond to more suitable food portions for customers. Specific forms of presentation which isolate the best parts of fish (gutted head off, gutted off peeled, wings or fillets) are associated with higher prices. The relationship between being gutted and prices is less clear as it is non-significant or negative for some species. Not surprisingly, lobsters and crabs are sold for a lower price when they are in pieces rather than whole, as crustaceans sold in

[10] This percentage is computed as (0.659-0.614)/(0.659-0.481)*100.

[11] Detailed results for all other species are reported in the Online Appendix.

pieces are those which have been damaged. Finally, the lowest quality is most often related to a lower price.

The introduction of unobserved heterogeneity changes the effect of some fish characteristics in a sizable way for several species. For instance, for cuttlefish, medium quality fish (grade A) is 33.0% less expensive than extra quality fish (grade E) when unobserved heterogeneity terms are omitted, but it is only 11.0% less expensive when seller-buyer fixed effects are introduced. There is a similar pattern for hake when considering the difference between low and extra quality fish (grades B and E), the respective figures being 50.5% and 38.3%. For cod, fillets are 63.7% more expensive than whole fish when unobserved heterogeneity terms are omitted, but they are only 16.9% more expensive when seller-buyer fixed effects are introduced. By contrast, for ray, gutted fish is only 10.5% more expensive than whole fish when unobserved heterogeneity is omitted, but it is 22.8% more expensive when seller-buyer fixed effects are introduced into the regression.

Differences can be explained by some unobserved heterogeneity among buyers in the willingness to pay correlated with presentation category, as there are different types of buyers such as primary processors, multiple grocers or mongers, and different downstream markets where buyers resell fish. They can also be explained by some unobserved heterogeneity among sellers correlated with both the presentation category and unobserved fish quality, as vessels use different types of fishing gear. Note that there can be some match effects as some specific buyers may have experience with the unobserved quality of fish sold by specific sellers when they are in a specific form.[12]

We also evaluate the explanatory power of unobserved heterogeneity terms for every species. Figure 3 reports, for every species, the R^2 obtained when unobserved heterogeneity is not taken into account, the R^2 increase when seller and buyer fixed effects are added to the specification, and the R^2 increase when seller-buyer fixed effects are considered instead of seller and buyer fixed effects. The R^2 obtained when unobserved heterogeneity is not taken into account is quite high, with an average of 0.47, but it varies across species. Among species with a significant market share, it is only 0.27 for mackerel, but it reaches 0.70 for Norway lobster (frozen).

[Insert Figure 3]

The explanatory power of seller and buyer fixed effects is relatively high as well, since the R^2 increases on average by 0.20 when they are introduced in the regression. The R^2 increase varies across species, from as little as 0.06 for seabass (line-caught), up to 0.37 for cuttlefish. Finally, the

[12] We tried to enrich our analysis by assessing whether estimated seller, buyer and match effects are correlated with some of buyer, seller and match characteristics that we could derive from our data. More precisely, buyers were characterized with their total number of transactions, their total purchase value, the number of sellers from whom they purchased fish. Sellers were characterized with their total number of transactions, their total sales value, the number of buyers to whom they sold fish. Finally, we also characterized matches with their number of transactions and their total sales. We then computed for each species the correlations between buyer fixed effects and buyer characteristics, seller fixed effects and seller characteristics, and match effects and match characteristics. Results, not reported but available upon request, show that all these correlations are weak.

explanatory power of match effects is significant, but not large. When introducing seller-buyer fixed effects instead of seller and buyer fixed effects in the regression, the R^2 increases on average by 0.06. The R^2 increase is only 0.02 for Norway lobster (live or frozen), but reaches 0.11 for ling.

4.2. Variance analysis of fish prices for all species

Another way to assess the importance of the different kind of effects in explaining fish price variations is to conduct a variance analysis of the most general specification including fish characteristics, time fixed effects, seller fixed effects, buyer fixed effects and match effects (equations 3a and 3b).[13] An advantage of this approach is that we can assess the respective importance of every kind of effect in explaining variations in fish prices from a single regression involving all the explanatory terms. Therefore, the explanatory power of the different effects deduced from the results does not depend on the order in which the explanatory terms are added in the regression as is the case when considering increases in R-square.

In our approach, a match effect is estimated as the average of price residuals at the match level once fish, seller and buyer effects have been netted out (see Appendix A for more details). When there is only one transaction for a match, the estimated match effect is the single price residual. It becomes clear that there is an identification issue as the estimated match effect captures both the true match effect and the noise specific to the price of the transaction. To overcome this issue, we only consider in our variance analysis transactions for matches with at least two transactions. As a robustness check, we replicated the analysis when further restricting the sample to transactions for matches with at least five or ten transactions. We found a small explanatory power of matches, but otherwise conclusions remain qualitatively similar.[14]

Table 5 reports, for every kind of factor (fish characteristics, time effects, seller effects, buyer effects, match effects and residuals), the ratio between the variance of its effect deduced from the regression results and the variance of the logarithm of fish prices. We also report the sum of covariance terms divided by the variance of the logarithm of fish prices, so that the sum of all terms expressed in percent on each row of the table is 100%. The higher is the variance ratio for a given kind of effects, the higher is the explanatory power of the related explanatory terms.

[Insert Table 5]

As expected, the overall explanatory power of fish characteristics is high, as the average variance ratio for fish characteristics is 32.0%. There are large variations across species as the variance ratio is

[13] Match effects are obtained by further estimating equation (3b), as explained in Appendix A. Note also that our regressions and variance analysis are conducted at the transaction level. In that perspective, pairs of sellers and buyers characterized by more transactions have more weight than others, as they are involved in more observations. At the same time, it makes sense as we are interested in price variations across transactions.

[14] These additional results are available upon request.

only 7.9% for squid and below 15% for horse mackerel, sand sole, tub gurnard, ling, grey mullet and mackerel. Conversely it is as high as 61.3% for Norway lobster (frozen) and above 40% for 16 additional species. Two groups of species for which the role of fish characteristics is important may be distinguished. The first one comprises high-price products such as Norway lobster (frozen or live), line-caught seabass, turbot or monkfish. For these species, fish having the best characteristics in terms of freshness and size are purchased at very high prices to be served in high-quality restaurants. The second group includes low-price products like cuckoo ray, ray, haddock, red gurnard, plaice or common dab. For them, it is essentially large-size fish that are purchased at higher prices.

The explanatory power of time fixed effects is lower but it is still significant as the corresponding average variance ratio is 10.4%. In particular, it is sizable for lobster (33.1%), squid (24.0%), line-caught seabass (21.2%), live Norway lobster (20.8%) and to a lesser extent non line-caught seabass (15.5%). A common characteristic of these species is that they are expensive, since they are sold for a price above 10 euros per kilogram (except squid whose price is 7.4 euros per kilogram). The substantial variations in prices of these high-quality products are related to the seasonality of consumption. The demand for products such as lobster and seabass is higher during summer. This is also true during Christmas holidays and fish catches are not important enough to meet the demand during that period. Conversely, the contribution of time effects to total variance is less than 5% for low-price species (less than 3 euros per kilogram) such as spotted ray, thornback ray, pouting, common dab, ray, place, tub gurnard or red gurnard.

Overall, unobserved heterogeneity related to buyers, sellers and their matches has a high explanatory power for many species, the average variance ratio for the sum of all the unobserved heterogeneity terms being 26.8%. This percentage is very high for tub gurnard (63.7%), sand sole (51.1%) and horse mackerel (50.0%). It is also important for cuttlefish (50.8%), octopus (38.3%) and squid (34.0%) which are three substitutable species. It is possible that the same buyers participate to the auctions for these three species and that they strongly influence the formation of prices. By contrast, the role of unobserved heterogeneity is much lower for high-price products such as sole (18.3%), monkfish (17.3%), frozen Norway lobster (14.3%), live Norway lobster (12.3%) or line-caught seabass (9.3%).

Buyer heterogeneity is the main unobserved term affecting prices. The average variance ratio of buyer effects is larger than that of seller effects for every species, and it is larger than that of match effects for every species except one. The average variance ratio of buyer effects is 22.1% compared to 7.7% for seller effects and 4.2% for match effects. The explanatory power of buyer effects is larger for some species for which fish characteristics and time do not play a significant role. This is the case for grey mullet (57.8%), mackerel (57.8%) and tub gurnard (46.2%). These three species have very low average prices (comprised between 1.5 and 2.9€ per kilogram) and are not subject to seasonal variability in supply as fish is caught the whole year and mostly purchased by wholesalers. The same low-price species are characterized by seller effects with a large explanatory power. Their contribution is 67.6% for grey mullet, 36.3% for horse mackerel and 35.7% for mackerel.[15] These species are harvested either by large trawlers or small-scale vessels such as purse-seiners, gill-netters or liners which differ in their production costs.

Finally, the contribution of match effects remains quite low as the related variance ratio never exceeds 7%. The highest values of this ratio are, by decreasing order, 6.9% for ling, 6.4% for meagre and dogfish, 6.1% for grey mullet, 6% for mackerel and pollack. These fish species are characterized by rather low average prices and their fish characteristics have a limited explanatory power (the largest variance ratio of fish characteristics being for dogfish at 25%). Interestingly, the influence of match effects is the smallest for line-caught seabass (2.5%), live Norway lobster (1.8%) and frozen Norway lobster (1.6%), which are three expensive species. The main explanation for this pattern is that our sample consists in transactions at auctions for which there cannot be specific arrangements between buyers and sellers. For high-quality species in particular, the demand is expected to be large and to come from the entire country, especially during festive periods when consumers' willingness to pay is high.

5. Conclusion

Hedonic price regressions introduced by Rosen (1974) rest on the assumption that the price of a good with given attributes is fixed at a unique value depending on supply and demand when there is perfect competition. This is not the case in practice because of unobservable quality attributes and imperfections on the market such a rationing or spatial and informational frictions, especially when agents are heterogeneous. Accordingly, both buyer and seller characteristics are expected to affect prices on agricultural markets.

In this paper, we investigated to what extent the valuation of fish observable attributes and fish price variations are related to the unobserved heterogeneity of sellers, buyers, and specific matches between sellers and buyers. This unobserved heterogeneity is taken into account in hedonic price regressions with series of fixed effects using an approach initially developed in labor economics to study the formation of wages. Estimations were conducted separately for most fish and crustacean species with a significant market share using a unique exhaustive dataset containing some information on all transactions occurring in French fish markets over the 2002-2007 period.

Our main results are that when unobserved heterogeneity terms are included in hedonic price regressions, the effects of quality-related fish characteristics change significantly for some species. A

[15] The contribution of seller effects is as high as 117.2% for horse mackerel, and thus above 100%, but the sum of covariance terms has a contribution of -107.8%.

variance analysis also shows that, on average, fish characteristics are the main factor explaining fish price variations. Nevertheless, time and buyer effects also play a significant role. Finally, we find that the explanatory power of match effects is rather small, which is consistent with the auction system preventing specific deals between sellers and buyers.

It is likely that the influence of buyers and sellers on fish prices depends on the market conditions underlying sales. In particular, future research could assess whether match effects play a more important role for transactions made hand to hand than for transactions through auctions. When sales are made through bilateral bargaining, match effects may even evolve over time as trust is developed between buyers and sellers through repeated transactions. However, taking this into account would require an extension of our empirical framework to incorporate time-varying match effects.

A final comment is that we have examined production prices in our paper. One may want to apply an approach similar to ours to consumption prices in supermarkets. Indeed, one can draw a parallel between our setting with vessels and buyers and a framework with brands and consumers. Such an analysis can be conducted only if one knows exactly which brands are purchased by consumers and consumers can be tracked across their purchases. This may become a promising line of research if bar codes data are someday coupled with customer loyalty cards.

References

Abowd J., Kramarz F., Margolis D., (1999), “High wage workers and high wage firms”, *Econometrica*, vol. 67, pp. 251-233.

Abowd J., Creecy R., Kramarz F., (2002), “Computing person and firm effects using linked longitudinal employer-employee data”, *mimeo*, Cornell University.

Alfnes F., Guttormsen A., Steine G., Kolstad K., (2006), “Consumers’ willingness to pay for the color of salmon: A choice experiment with real economic incentives”, *American Journal of Agricultural Economics*, vol. 88, pp. 1050-1061.

Asche F., Guillen J., (2012), “The importance of fishing method, gear and origin: The Spanish hake market”, *Marine Policy*, vol. 36, pp. 365-369.

Asche F., Larsen T., Smith M., Sogn-Grundvag, Young J., (2015), “Pricing of eco-labels with retailer heterogeneity”, *Food Policy*, 53, pp. pp. 82-93.

Asche F., Chen Y., Smith, M., (2015), “Economic incentives to target species and fish size: prices and fine-scale product attributes in Norwegian fisheries”, *ICES Journal of Marine Science*, vol. 72, pp. 733-740.

Ashenfelter O., (2008), “Predicting the quality and prices of Bordeaux wine”, *Economic Journal*, vol. 118, F175-F184.

Bajari P., Benkard C., (2005), “Demand Estimation with Heterogeneous Consumers and Unobserved Product Characteristics: A Hedonic Approach”, Journal of Political Economy, vol. 113, pp. 1239-1276.

Card D., Krueger A., (1992), “School quality and black-white relative earnings: a direct assessment”, *Quarterly Journal of Economics*, vol. 107, pp. 151-200.

Cirillo P., Tedeschi G., Gallegati M., (2012), “The Boulogne fish market: the social structure and the role of loyalty”, *Applied Economics Letters*, vol. 19, pp. 1075-1079.

Combris P., Lecocq S., Visser M., (1997), “Estimation of a hedonic price equation for Bordeaux Wine: does quality matter?”, *Economic Journal*, vol. 107, pp. 390-402.

France Agrimer, (2012), *Les filières pêche et aquaculture en France*, chiffres-clés, Paris, 36 p.

Gobillon L., Wolff F.C., (2016), “Evaluating the law of one price using micro panel data: The case of the French fish market”, *American Journal of Agricultural Economics*, vol. 98, pp. 134-153.

Guillotreau P., Jiménez-Toribio R., (2011), “The price effect of expanding fish markets”, *Journal of Economic Behavior and Organization*, vol. 79, pp. 211-225.

Guillotreau P., Le Grel L., Simioni M., (2005), “Price-Cost Margins and Structural Change: Sub-Contracting within the Salmon Marketing Chain”, *Review of Development Economics*, vol. 9, pp. 581-597.

Kirman A., Vriend, (2011) N., “Evolving market structure: An ACE model of price dispersion and loyalty”, vol. 25, pp. 459-502.

Kristofersson D., Rickertsen K., (2004), “Efficient estimation of hedonic inverse input demand systems”, *American Journal of Agricultural Economics*, vol. 86, pp. 1127-1137.

Kristofersson D., Rickertsen K., (2007), “Hedonic price models for dynamic markets”, *Oxford Bulletin of Economics and Statistics*, vol. 69, pp. 387-412.

Kristofersson D., Rickertsen K., (2009), “Highgrading in Quota-Regulated Fisheries: Evidence from the Icelandic Cod Fishery”, *American Journal of Agricultural Economics*, vol. 91(2), pp. 335-346.

Lach S., (2002), “Existence and persistence of price dispersion: An empirical analysis”, *Review of Economics and Statistics*, vol. 84, pp. 433-444.

Lee M.Y., (2014), “Hedonic Pricing of Atlantic Cod: Effects of Size, Freshness, and Gear”, vol. 29(3), pp. 259-277.

McConnell K., Strand I., (2000), "Hedonic prices for fish: Tuna prices in Hawaii", *American Journal of Agricultural Economics*, vol. 82, pp. 133-144.

Moulton B., (1990), "An Illustration of a Pitfall in Estimating Effects of Aggregate Variables on Micro Unites", vol. 72, pp. 334-338.

Nerlove M., (1995), "Hedonic price functions and the measurement of preferences: the case of Swedish Wine Consumers", *European Economic Review*, vol. 39, pp. 1697-1716.

Pascoe S., Coglan L., (2002), "The Contribution of Unmeasurable Inputs to Fisheries Production: An Analysis of Technical Efficiency of Fishing Vessels in the English Channel", *American Journal of Agricultural Economics*, vol. 84, pp. 585–597.

Roheim C., Asche F., Insignares J., (2011), "The elusive price premium for ecolabelled products: Evidence from seafood in the UK market", *Journal of Agricultural Economics*, vol. 62, pp. 655-668.

Roheim C., Gardiner L., Asche F., (2007), "Value of brands and other attributes: Hedonic analysis of retail frozen fish in the UK", *Marine Resource Economics*, vol. 22, 239-253.

Rosen S., (1974), "Hedonic prices and implicit markets: product differentiation in pure competition", *Journal of Political Economy*, vol. 88, pp. 34-55.

Sorensen A., (2000), "Equilibrium Price Dispersion in Retail Markets for Prescription Drugs", *Journal of Political Economy,* vol. 108, pp. 833-850.

Sørensen T., Vejlin R., (2013), "The importance of worker, firm and match effects in the formation of wages", *Empirical Economics*, vol. 45, pp. 435-464.

Stanley L.R., Tschirhart J., (1991), "Hedonic prices for a non-durable good: The case of breakfast cereals", *Review of Economics and Statistics*, vol. 73, pp. 537-541.

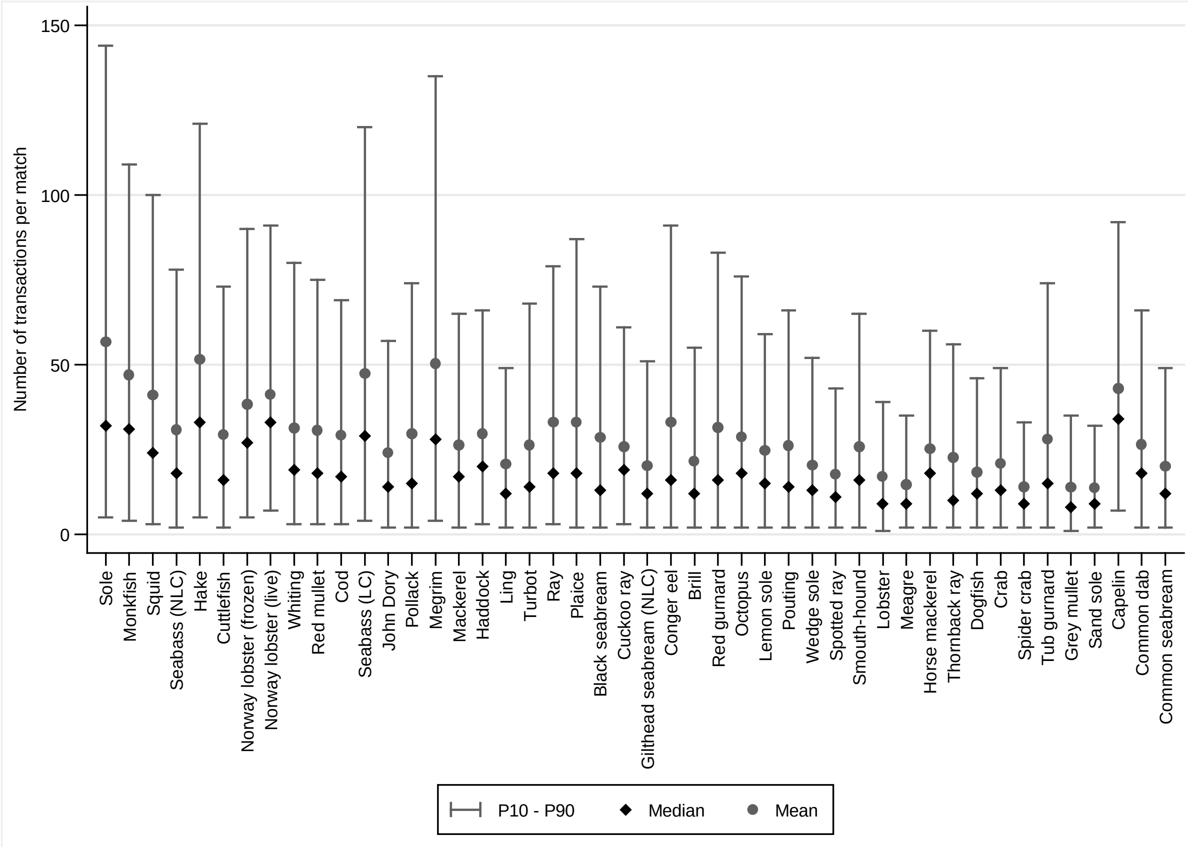
Viswanathan K., Ishak O., Jeon Y., Kirkley J., Squires D., Susilowati I., (2001), "Fishing Skill in Developing Countries: The Kedah, Malaysia Trawl Fishery", *Marine Resource Economics*, vol. 16, pp. 293-314.

Wolff F.C., Squires D., Guillotreau P., (2013), "The firm's management in production: Management, firm, and time effects in an Indian Ocean tuna fishery", *American Journal of Agricultural Economics*, vol. 95, pp. 547-567.

Woodcock S.D., (2008), "Wage differentials in the presence of unobserved worker, firm, and match heterogeneity", *Labour Economics*, vol. 15, pp. 771-793.

Woodcock S.D., (2015), "Match effects", *Research in Economics*, vol. 69, pp. 100-121.

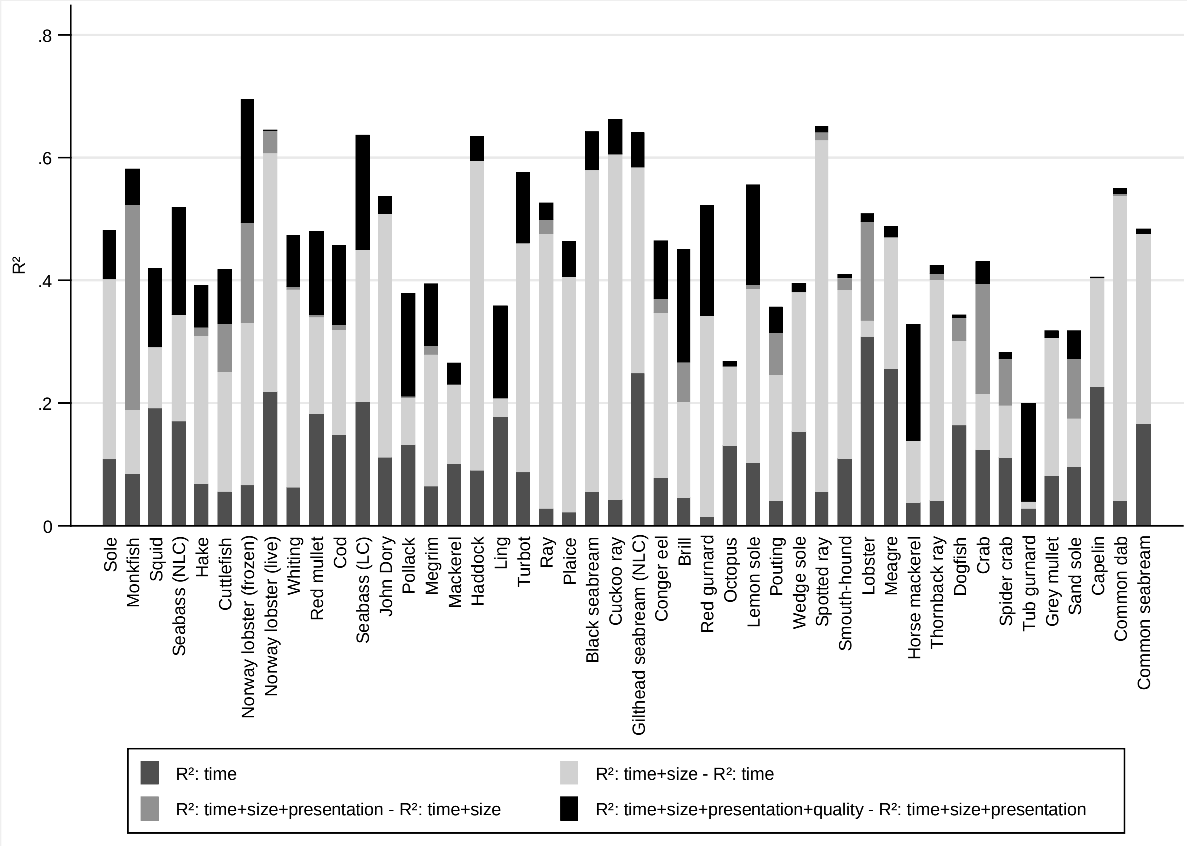
Figure 1. Number of transactions per match



Source: RIC 2002-2007, authors' calculations.

Note: NLC = not line-caught, LC = line-caught. The number of transactions per match for a given species is computed by averaging the number of transactions for every pair of buyer and seller involved in a transaction of fish of that species. The graph reports the median with a diamond, the mean with a dot and the range between the first and last decile with an interval. Fish species are sorted by decreasing contribution to total sales.

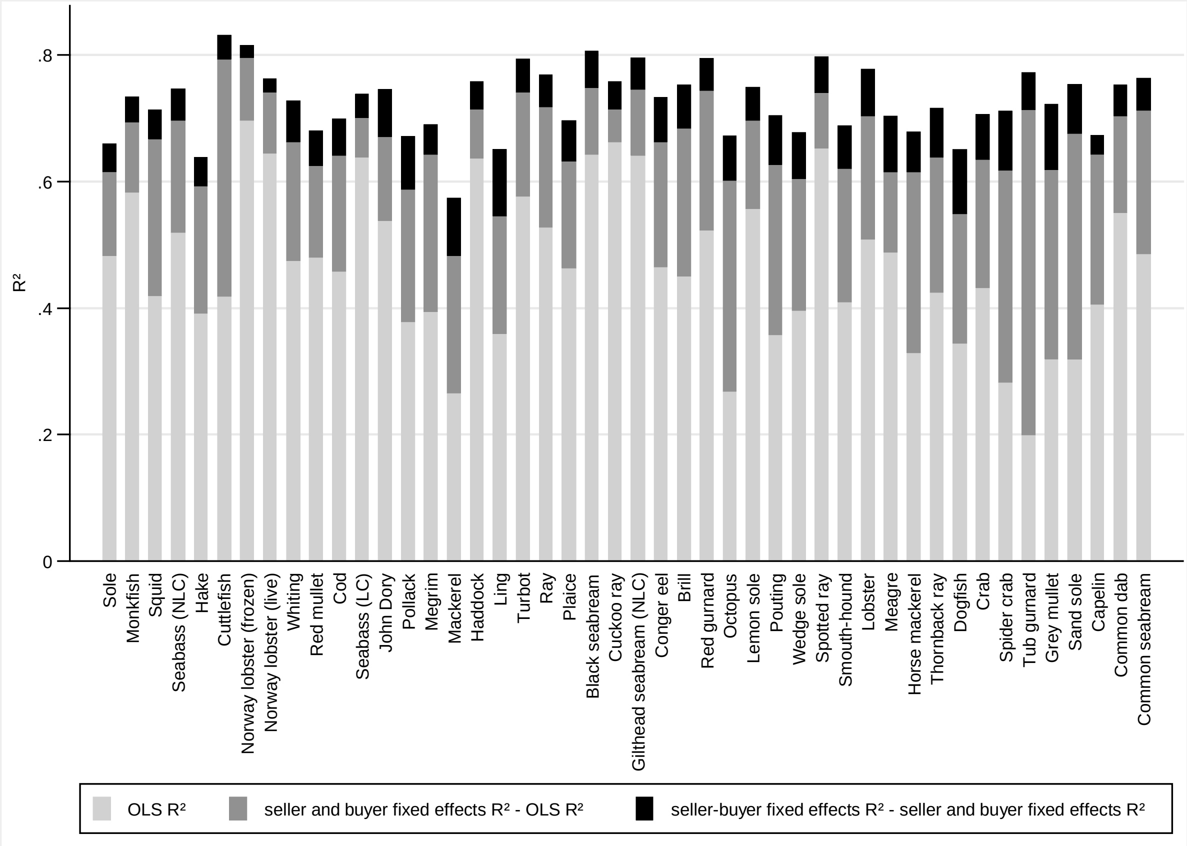
Figure 2. Contributions of time, size, presentation and quality to the R²



Source: RIC 2002-2007, authors' calculations.

Note: NLC = not line-caught, LC = line-caught. "R^2: time" gives the R-square of a regression involving only time dummy variables as controls. "R^2: time+size" gives the R-square of a regression involving time and size dummy variables as controls. "R^2: time+size+presentation" gives the R-square of a regression involving time, size and presentation dummy variables as controls. "R^2: time+size+presentation+quality" gives the R-square of a regression involving time, size, presentation and quality dummy variables as controls. We report in the graph "R^2: time" and the successive increases in R-square when additional variables are added in the regression. Fish species are sorted by decreasing contribution to total sales.

Figure 3. Contributions of seller, buyer and seller-buyer fixed effects to the R²



Source: RIC 2002-2007, authors' calculations.
Note: NLC = not line-caught, LC = line-caught. "OLS R^2" gives the R-square of a specification estimated with OLS that includes the explanatory variables related to time, size, presentation and quality but not any unobserved heterogeneity term. "seller and buyer fixed effects R^2" gives the R-square of a specification that additionally includes seller and buyer fixed effects. "seller-buyer fixed effects R^2" gives the R-square of a specification that includes fixed effects for each pair of seller and buyers, but not seller and buyer fixed effects. We report in the graph "OLS R^2" as well as the successive increases in R-square when seller and buyer fixed effects, and then seller-buyer fixed effects, are added in the regression. Fish species are sorted by decreasing contribution to total sales.

Table 1. Descriptive statistics on transactions by species

Fish species	Sales (in million euros)		Price per kilogram (in euros)		Transactions	
	Total amount	Percentage	Mean	St. dev.	Number	Percentage
Sole	43,603.1	14.57	12.65	4.61	1,457,282	10.01
Monkfish	36,815.7	12.30	5.79	2.44	863,500	5.93
Squid	18,755.3	6.27	7.37	3.75	549,083	3.77
Seabass (NLC)	16,931.1	5.66	10.55	4.92	705,547	4.84
Hake	16,166.3	5.40	5.19	2.37	1,206,817	8.29
Cuttlefish	15,726.9	5.26	2.99	2.41	423,015	2.90
Norway lobster (frozen)	14,963.7	5.00	9.43	4.79	215,206	1.48
Norway lobster (live)	14,243.2	4.76	11.03	4.74	348,816	2.39
Whiting	11,187.8	3.74	2.38	1.48	526,094	3.61
Red mullet	11,043.7	3.69	7.08	3.89	690,916	4.74
Cod	9,408.0	3.14	4.13	1.66	260,137	1.79
Seabass (LC)	8,226.9	2.75	14.55	3.98	239,293	1.64
John Dory	7,583.6	2.53	9.34	3.91	278,069	1.91
Pollack	6,836.4	2.28	4.36	2.08	466,037	3.20
Megrim	5,065.5	1.69	4.60	2.49	290,904	2.00
Mackerel	4,211.3	1.41	1.52	1.12	466,378	3.20
Haddock	4,109.3	1.37	1.80	0.86	154,963	1.06
Ling	4,032.2	1.35	2.69	0.91	175,774	1.21
Turbot	3,957.4	1.32	14.67	5.78	338,921	2.33
Ray	3,604.4	1.20	2.89	1.42	347,955	2.39
Plaice	3,573.4	1.19	1.47	0.78	352,040	2.42
Black seabream	3,430.4	1.15	3.36	2.30	280,202	1.92
Cuckoo ray	2,801.3	0.94	1.80	0.85	111,493	0.77
Gilthead seabream (NLC)	2,522.5	0.84	9.78	5.84	185,221	1.27
Conger eel	2,343.2	0.78	2.20	1.39	349,239	2.40
Brill	2,291.8	0.77	9.86	3.91	319,475	2.19
Red gurnard	2,146.2	0.72	1.76	1.88	310,892	2.13
Octopus	2,139.2	0.71	3.15	2.01	177,485	1.22
Lemon sole	2,117.5	0.71	4.44	2.22	161,666	1.11
Pouting	1,680.1	0.56	0.86	0.67	335,741	2.31
Wedge sole	1,615.6	0.54	5.58	2.22	60,286	0.41
Spotted ray	1,572.2	0.53	3.03	1.20	92,074	0.63
Smooth-hound	1,523.7	0.51	1.39	0.80	158,639	1.09
Lobster	1,461.4	0.49	20.89	6.75	86,372	0.59
Meagre	1,459.3	0.49	4.71	3.16	109,290	0.75
Horse mackerel	1,413.4	0.47	0.95	0.73	181,585	1.25
Thornback ray	1,387.3	0.46	3.17	1.52	138,070	0.95
Dogfish	1,354.5	0.45	0.62	0.45	248,799	1.71
Crab	1,262.9	0.42	2.59	1.31	101,098	0.69
Spider crab	1,020.2	0.34	2.00	1.15	102,430	0.70
Tub gurnard	971.1	0.32	2.85	3.24	176,692	1.21
Grey mullet	782.3	0.26	1.51	1.12	133,904	0.92
Sand sole	668.5	0.22	6.06	2.65	65,692	0.45
Capelin	477.1	0.16	1.56	0.87	180,664	1.24
Common dab	397.8	0.13	1.18	0.87	67,961	0.47
Common seabream	342.3	0.11	7.38	5.96	73,041	0.50

Source: RIC 2002-2007, authors' calculations.

Note: NLC = not line-caught, LC = line-caught. The total amount of sales is obtained summing the sale prices of all fish lots and the corresponding percentage for a given species is computed as the share of sales among all species. Price per kilogram is computed dividing the sale price of the fish lot involved in the transaction by the quantity of fish included in that lot. The mean and standard deviation are computed using all the fish lots involved in transactions of a given species. The percentage of transactions for a given species is also the share of transactions among all species. Fish species are sorted by decreasing contribution to total sales.

Table 2. Descriptive statistics of the market

Fish species	Number of sellers	Average number of sellers per buyer	Number of buyers	Average number of buyers per seller	Number of matches
Sole	3,216	40,26	3,023	42,83	129,482
Monkfish	2,339	34,72	2,786	29,15	81,208
Squid	2,195	29,88	2,787	23,53	65,587
Seabass (NLC)	3,543	29,63	2,986	35,15	104,971
Hake	2,254	44,08	2,745	36,19	99,348
Cuttlefish	3,108	22,33	2,672	25,97	69,389
Norway lobster (frozen)	489	40,03	962	20,35	19,577
Norway lobster (live)	390	65,22	959	26,52	25,437
Whiting	2,444	30,55	2,237	33,38	74,671
Red mullet	2,768	34,11	2,884	32,73	94,403
Cod	1,780	21,00	1,642	22,76	37,376
Seabass (LC)	1,186	22,23	1,464	18,01	26,361
John Dory	2,178	22,69	2,418	20,44	49,413
Pollack	2,695	28,61	2,153	35,81	77,092
Megrim	1,007	30,48	1,948	15,76	30,694
Mackerel	2,553	27,96	2,895	24,66	71,383
Haddock	810	24,01	1,163	16,72	19,449
Ling	1,723	19,45	1,668	20,09	33,517
Turbot	2,898	20,62	2,476	24,13	59,753
Ray	2,576	19,96	1,996	25,76	51,423
Plaice	3,334	17,16	2,433	23,51	57,205
Black seabream	2,462	21,77	2,135	25,11	53,610
Cuckoo ray	847	18,87	762	20,97	15,981
Gilthead seabream (NLC)	1,902	19,29	1,916	19,15	36,699
Conger eel	2,432	23,72	2,042	28,25	57,681
Brill	2,742	22,74	2,553	24,42	62,352
Red gurnard	2,340	21,84	2,606	19,61	51,107
Octopus	1,726	15,36	1,638	16,19	26,513
Lemon sole	1,361	20,21	1,599	17,20	27,510
Pouting	2,477	23,26	2,013	28,62	57,621
Wedge sole	446	23,30	461	22,54	10,392
Spotted ray	1,069	17,81	827	23,02	19,037
Smooth-hound	2,114	12,10	1,149	22,27	25,587
Lobster	1,453	14,04	1,684	12,11	20,394
Meagre	1,039	22,37	667	34,84	23,238
Horse mackerel	1,845	15,33	1,999	14,15	28,278
Thornback ray	1,692	17,47	1,153	25,64	29,563
Dogfish	2,753	17,80	2,119	23,13	49,012
Crab	1,116	17,08	1,418	13,44	19,061
Spider crab	1,304	18,17	1,294	18,31	23,699
Tub gurnard	1,894	17,29	1,854	17,66	32,747
Grey mullet	2,419	14,78	2,134	16,75	35,749
Sand sole	1,213	12,48	858	17,64	15,138
Capelin	210	61,25	705	18,24	12,862
Common dab	768	13,45	511	20,21	10,328
Common seabream	343	37,09	659	19,30	12,721

Source: RIC 2002-2007, authors' calculations.

Note: NLC = not line-caught, LC = line-caught. For a given species, the number of sellers (resp. buyers) is computed summing all sellers (resp. buyers) involved in a transaction of fish belonging to that species. The average number of sellers per buyer is computed as the number of sellers divided by the number of buyers. Fish species are sorted by decreasing contribution to total sales.

Table 3. Results of hedonic price regressions for sole and monkfish

A. Sole

Explanatory variables		OLS	Seller and buyer fixed effects	Seller-buyer fixed effects
Size	2	0.059	0.028	0.028
(ref: 1 Large)		(0.059)	(0.029)	(0.029)
	3	-0.075**	-0.067***	-0.065**
		(0.031)	(0.024)	(0.024)
	4	-0.193***	-0.197***	-0.195***
		(0.038)	(0.023)	(0.024)
	5 (small)	-0.515***	-0.537***	-0.536***
		(0.044)	(0.030)	(0.031)
Presentation	Gutted	0.076**	0.012	0.009
(ref: Whole)		(0.029)	(0.016)	(0.017)
Quality	A	-0.135***	-0.062***	-0.058**
(ref: Extra)		(0.034)	(0.020)	(0.022)
	B (low)	-0.680***	-0.579***	-0.582***
		(0.070)	(0.042)	(0.042)
Time fixed effects		YES***	YES***	YES***
Seller fixed effects		NO	YES***	NO
Buyer fixed effects		NO	YES***	NO
Seller-buyer fixed effects		NO	NO	YES***
Number of observations		1,457,282	1,457,282	1,457,282
R^2		0.481	0.614	0.659

B. Monkfish

Explanatory variables		OLS	Seller and buyer fixed effects	Seller-buyer fixed effects
Size	2	0.014	0.018*	0.018*
(ref: 1 Large)		(0.018)	(0.010)	(0.010)
	3	-0.045***	-0.072***	-0.073***
		(0.017)	(0.013)	(0.013)
	4	-0.112***	-0.134***	-0.133***
		(0.012)	(0.010)	(0.010)
	5 (small)	-0.365***	-0.365***	-0.360***
		(0.020)	(0.020)	(0.020)
Presentation	Gutted	-0.048	0.150***	0.155***
(ref: Whole)		(0.057)	(0.034)	(0.032)
	Gutted head-off	0.546***	0.711***	0.691***
		(0.066)	(0.043)	(0.041)
	Gutted head-off, peeled	0.726***	1.003***	0.985***
		(0.062)	(0.044)	(0.043)
	Pieces	0.743***	0.834***	0.824***
		(0.058)	(0.039)	(0.040)
Quality	A	-0.090***	-0.018	-0.020
(ref: Extra)		(0.009)	(0.013)	(0.015)
	B (low)	-0.608***	-0.517***	-0.508***
		(0.086)	(0.069)	(0.073)
Time fixed effects		YES***	YES***	YES***
Seller fixed effects		NO	YES***	NO
Buyer fixed effects		NO	YES***	NO
Seller-buyer fixed effects		NO	NO	YES***
Number of observations		863,500	863,500	863,500
R^2		0.582	0.693	0.734

Source: RIC 2002-2007, authors' calculations.

Note: standard errors clustered at the size-presentation-quality level are in parentheses; ***: significant at 1%, **: significant at 5%, *: significant at 10%. For sets of fixed effects, the level of joint significance is also reported. Size categories are in decreasing order of size. "OLS" gives the estimation results for a simple linear specification in which no unobserved heterogeneity term is introduced; "Seller and buyer fixed effects" gives the estimation results for a linear specification that includes both seller and buyer fixed effects; finally "Seller-buyer fixed effects" gives the estimation results for a specification where fixed effects are introduced for each pair of buyer and seller.

Table 4 Summary of hedonic estimation results by species

Fish species	Size (ref: 1)					Presentation (ref: whole)								Quality (ref: Extra)	
	2	3	4	5	6	Gutted	Gutted head off	Gutted head off peeled	Wings	Fillets	Pieces	Pieces crustacean	Whole crustacean	A	B
Sole	ns	--	---	---		ns								--	---
Monkfish	+	---	---	---		+++	+++	+++			+++			ns	---
Squid	+++	+	Ns	---										---	---
Seabass (NLC)	---	---				---								---	---
Hake	---	---	---	---		ns				+++				ns	---
Cuttlefish	ns	---	---	--		+++	+++				---			---	---
Norway lobster (frozen)	---	---	---								-		+++	ns	---
Norway lobster (live)	---	---	---										+++	---	---
Whiting	---	---	---			+++								---	---
Red mullet	--	---	---			ns								---	---
Cod	+++	---	---	---		--				+++				---	---
Seabass (LC)	---	---												---	---
John Dory	---	---	---			ns								ns	---
Pollack	ns	---	---			+++								---	---
Megrim	---	---	---			ns								---	---
Mackerel	---	---	---											--	ns
Haddock	---	---	---			ns								ns	---
Ling	+++	+++				ns								--	---
Turbot	---	---	---			ns								---	---
Ray	---	---	---			+++			+++					ns	---
Plaice	---	---	---			+++								ns	---
Black seabream	---	---	---											---	---
Cuckoo ray	---	---	---			ns								ns	---
Gilthead seabream (NLC)	---	---	---											ns	---
Conger eel	---	---	---			+++								---	---
Brill	---	---				ns								---	---
Red gurnard	---	---	---											---	---
Octopus	---	---	---	---	---									---	---
Lemon sole	---	---				ns								---	---
Pouting	---	---	---			+++								ns	---
Wedge sole	--					ns								ns	---
Spotted ray	---	---	---			+++								ns	---
Smouth-hound	---	---	---	---		++								ns	---
Lobster	+++	+++										---	ns	ns	---
Meagre	---	---				---								---	---
Horse mackerel	---	---	---	---										-	ns
Thornback ray	---	---	---			+			+++					++	ns
Dogfish	---	---	---			+++		+++						---	---
Crab	---						+++					---	ns	---	---
Spider crab	---											---	--	---	---
Tub gurnard	---					++								---	---
Grey mullet	---	---	---											ns	---
Sand sole	---					ns								ns	---
Capelin	---	---												+	---
Common dab	---					+++								---	---
Common seabream	---	---	---											ns	ns

Source: RIC 2002-2007, authors' calculations.

Note: estimates from seller-buyer fixed effect models, with standard errors clustered at the size-presentation-quality level. ---: negative and significant at 1%; --: negative and significant at 5%; - negative and significant at 10%; +++: positive and significant at 1%; ++: positive and significant at 5%; + positive and significant at 10%; ns: not significant. NLC = not line-caught, LC = line-caught. Fish species are sorted by decreasing contribution to total sales.

Table 5. Variance decomposition of fish prices (using only transactions in matches with at least two observations)

Fish species	Variance of log-price	Fish characte-ristics	Time	Unobserved heterogeneity				Sum of co-variance terms	Residual
				All	Sellers	Buyers	Matches		
Sole	0.162	36.2%	10.5%	18.3%	2.1%	11.6%	3.6%	1.1%	34.9%
Monkfish	0.152	40.0%	10.0%	17.3%	2.3%	10.4%	3.2%	6.5%	27.6%
Squid	0.213	7.9%	24.0%	34.0%	4.9%	19.8%	3.5%	10.1%	29.8%
Seabass (NLC)	0.204	22.4%	15.5%	25.0%	5.1%	25.5%	3.6%	1.4%	26.5%
Hake	0.219	41.2%	5.9%	27.7%	6.7%	20.9%	3.8%	-15.5%	37.0%
Cuttlefish	0.455	32.8%	6.6%	50.8%	2.2%	42.5%	2.7%	-5.3%	18.5%
Norway lobster (frozen)	0.275	61.3%	7.8%	14.3%	2.7%	11.4%	1.6%	-3.6%	18.8%
Norway lobster (live)	0.178	48.1%	20.8%	12.3%	1.6%	10.9%	1.8%	-7.3%	24.2%
Whiting	0.503	32.5%	4.9%	25.4%	5.8%	15.0%	4.6%	8.4%	28.8%
Red mullet	0.490	25.1%	18.2%	19.1%	5.9%	11.1%	4.3%	2.0%	33.3%
Cod	0.182	32.7%	10.7%	23.6%	3.9%	13.8%	4.2%	2.6%	32.0%
Seabass (LC)	0.088	42.1%	21.2%	9.3%	1.8%	5.8%	2.5%	-0.7%	27.3%
John Dory	0.252	38.0%	8.4%	18.9%	2.7%	12.9%	4.7%	4.8%	28.4%
Pollack	0.252	18.5%	14.6%	27.8%	8.0%	12.8%	6.0%	5.0%	35.1%
Megrim	0.406	32.2%	6.3%	29.0%	2.3%	22.5%	3.6%	1.0%	32.1%
Mackerel	0.650	14.9%	7.8%	29.4%	35.7%	57.8%	6.0%	-67.6%	45.4%
Haddock	0.302	46.8%	11.1%	10.9%	1.9%	7.7%	3.0%	4.1%	25.4%
Ling	0.131	11.7%	16.7%	28.1%	4.8%	17.0%	6.9%	4.5%	38.5%
Turbot	0.174	41.1%	7.8%	21.2%	2.2%	14.3%	3.5%	8.8%	22.3%
Ray	0.356	48.8%	3.0%	23.9%	3.0%	18.4%	3.4%	-1.2%	24.6%
Plaice	0.427	42.5%	2.2%	24.2%	3.3%	17.4%	4.3%	-2.1%	32.5%
Black seabream	0.707	44.2%	5.7%	16.8%	3.8%	11.2%	3.7%	10.2%	21.1%
Cuckoo ray	0.321	60.0%	5.1%	7.6%	1.9%	3.5%	2.9%	1.4%	25.4%
Gilthead seabream (NLC)	0.617	40.5%	16.8%	13.5%	4.1%	9.3%	3.4%	4.2%	21.7%
Conger eel	0.426	30.2%	5.5%	25.7%	3.4%	18.9%	4.7%	8.6%	28.7%
Brill	0.194	24.5%	3.4%	36.1%	3.7%	29.3%	4.6%	7.7%	26.8%
Red gurnard	0.830	45.4%	1.4%	25.6%	11.1%	19.3%	3.3%	-2.4%	21.9%
Octopus	0.467	27.1%	15.9%	38.3%	15.9%	24.5%	5.0%	-23.2%	34.9%
Lemon sole	0.364	34.9%	7.0%	19.5%	2.5%	13.0%	3.6%	12.4%	26.7%
Pouting	0.570	26.9%	3.7%	33.6%	3.7%	23.0%	5.3%	5.7%	31.7%
Wedge sole	0.189	20.7%	16.2%	28.5%	5.1%	23.0%	5.0%	-4.6%	34.5%
Spotted ray	0.280	46.4%	4.4%	13.9%	2.9%	6.1%	3.7%	14.4%	22.1%
Smooth-hound	0.458	35.5%	12.2%	28.2%	3.4%	17.9%	4.4%	-6.7%	33.3%
Lobster	0.103	16.3%	33.1%	23.8%	7.2%	16.4%	4.1%	-2.3%	25.1%
Meagre	0.674	20.8%	14.2%	20.4%	6.5%	9.2%	6.4%	10.8%	32.1%
Horse mackerel	0.564	10.7%	4.6%	50.0%	36.3%	117.2%	4.3%	-107.8%	34.8%
Thornback ray	0.364	36.3%	3.8%	31.6%	4.0%	20.1%	5.1%	-0.2%	30.9%
Dogfish	0.350	24.2%	15.9%	27.6%	3.2%	21.1%	6.4%	-9.2%	38.5%
Crab	0.335	27.6%	11.8%	26.0%	24.5%	30.4%	4.6%	-31.0%	32.0%
Spider crab	0.399	21.8%	12.3%	41.8%	6.5%	24.1%	5.8%	-2.9%	32.4%
Tub gurnard	1.167	11.5%	2.0%	63.7%	5.1%	46.2%	3.9%	6.6%	24.7%
Grey mullet	0.562	14.1%	5.2%	39.4%	67.6%	57.8%	6.1%	-82.5%	31.7%
Sand sole	0.284	11.3%	9.4%	51.1%	14.8%	24.5%	4.8%	7.8%	27.4%
Capelin	0.388	36.0%	21.8%	29.9%	0.7%	27.1%	2.7%	-21.5%	33.1%
Common dab	0.510	40.6%	3.6%	18.7%	3.3%	16.1%	3.2%	6.9%	26.3%
Common seabream	0.923	48.5%	9.2%	30.5%	2.5%	27.8%	3.6%	-16.7%	25.1%

Source: RIC 2002-2007, authors' calculations.

Note: NLC = not line-caught, LC = line-caught. "Variance of log-price" is the variance of the logarithm of the price computed from raw data. The other columns report the ratios (in percentage) between the variance of the quantity that is considered and the variance of the logarithm of the price. "Fish characteristics" refers to the sum of the effects of all fish characteristics; "time" refers to time effects; for "Unobserved heterogeneity, "All" refers to the sum of the seller fixed effects, buyer fixed effects and match effects, "Sellers" to seller fixed effects, "Buyer" to buyer fixed effects, "Matches" to match effects; "Residual" refers to the estimated residual of the linear specification. Fish species are sorted by decreasing contribution to total sales.

Appendix A. Estimation procedure

Estimating the model without match effects

When estimating equation (2), time effects can easily be taken into account with month-year dummy variables (the one for the first month being dropped to grant identification) as there are only 72 months of data. The main difficulty is that there are many seller and buyer fixed effects, so that a direct estimation of the model with dummy variables for the two sets of fixed effects is unfeasible in practice. However, since the number of sellers is not that high, we can include seller dummy variables to take into account the set of seller fixed effects (one being dropped for a seller that serves as a reference).[16]

We use the Frisch-Waugh theorem to deal with buyer fixed effects. We first sweep out buyer fixed effects using a within transformation in the buyer dimension. Ordinary Least Squares are used to recover the coefficients of fish characteristics as well as the month-year and seller fixed effects denoted respectively by $\hat{\beta}$, $\hat{\vartheta}_t$ and $\hat{\gamma}_j$. Estimators of buyer fixed effects denoted $\hat{\delta}_k$ can then be recovered from the second step of Frisch-Waugh theorem using the formula $\hat{\delta}_k = \sum_{i\in k}\left(P_i - X_i\hat{\beta} - \hat{\vartheta}_t - \hat{\gamma}_{j(i)}\right)/N_k$, where N_k is the number of transactions in which buyer k is involved.[17]

Estimation of the model with match effects

The parameters in equation (3a) are estimated using the Frisch-Waugh theorem. In a first step, variables are centered with respect to their mean computed at the level of the match between a seller and a buyer. This makes the terms μ_{jk} disappear and the resulting equation can be estimated using Ordinary Least Squares. This allows to recover some estimators of the coefficients of fish characteristics and month-year fixed effects denoted $\hat{\beta}$ and $\hat{\vartheta}_t$. An estimator of μ_{jk} denoted $\hat{\mu}_{jk}$ is given by the second step of Frisch-Waugh theorem using the formula $\hat{\mu}_{jk} = \sum_{i\in(j,k)}(P_i - X_i\hat{\beta} - \hat{\vartheta}_t)\,/\,N_{jk}$, where N_{jk} is the number of transactions between seller j and buyer k. We can then rewrite equation (3b) as:

$$\hat{\mu}_{jk} = \gamma_j + \delta_k + \eta_{jk} \tag{A1}$$

where $\eta_{jk} = \theta_{jk} + \hat{\mu}_{jk} - \mu_{jk}$ is the sum of the match effect and a sampling error arising from the fact that the dependent variable is an estimated parameter. Seller and buyer fixed effects can be taken into account with two sets of dummy variables. The resulting equation can then be estimated using Ordinary Least Squares, but this procedure is not efficient as it does not take properly into

[16] The identity of the seller does not matter since we do not make any comparison of estimated seller coefficients.

[17] No identification constraint is imposed on buyer fixed effects and they implicitly absorb the constant which is not identified separately from them.

account the sampling error on the dependent variable. Therefore, we prefer to use Weighted Least Squares where the weights are the number of transactions per match N_{jk}.[18]

As in the case of the model without match effects, parameters are estimated in two steps using the Frisch-Waugh theorem. Estimators of the seller and buyer fixed effects are denoted by $\hat{\gamma}_j$ and $\hat{\delta}_k$, respectively. Finally, the estimator of the match effect is given by the formula $\hat{\theta}_{jk} = \hat{\mu}_{jk} - \hat{\gamma}_j - \hat{\delta}_k$. Note that replacing $\hat{\mu}_{jk}$ by its expression yields $\hat{\theta}_{jk} = \sum_{i\in(j,k)} \hat{\epsilon}_{ijkt} / N_{jk}$, where $\hat{\epsilon}_i = P_i - X_i\hat{\beta} - \hat{\vartheta}_t - \hat{\gamma}_{j(i)} - \hat{\delta}_{k(i)}$. Hence, estimated match effects are simply averages of estimated residuals computed at the match level.

Appendix B. Sample restrictions

First, we exclude transactions with a missing buyer identifier (149,709 observations deleted).[19] Second, we delete observations corresponding to direct sales and restrict our attention to transactions at auctions (909,307 observations deleted).[20] Third, we keep only the 49 species for which there are more than 60,000 transactions over the period (2,197,513 observations deleted). Fourth, for each species, we exclude the few incoherent transactions with a negative total value or a negative quantity (30,382 observations deleted) as well as transactions with a price per kilogram in the bottom 0.1% or the top 0.1% to avoid potential outliers (63,971 observations deleted). Finally, in line with our empirical strategy, we keep for each species the largest group of well inter-connected sellers and buyers and exclude three species for which this group does not contain most of the observations (282,098 observations deleted).[21]

[18] For the sake of robustness, we also computed the weighted least square estimator proposed by Card and Krueger (1992) where the weights are the inverse of the first-stage variances. This approach is much more time-consuming because it involves computing the standard errors of estimated fixed effects. This approach leads to very similar results (available upon request).

[19] There are missing identifiers only for buyers. The identifier is always given for vessels involved in transactions.

[20] We eliminated direct sales because the fish price for such transactions is fixed in a very different way.

[21] The three fish species excluded from the sample are sardine (114,784 transactions), white seabream (75,279 transactions) and anchovy (72,884 transactions). For each of these three species, the share of transactions in the main group is 53.8%, 61.1% and 76.3%, respectively. For the remaining 46 species, only 19,151 transactions are excluded because they are not in the main group.