The effect of buyers and sellers on fish market prices

Laurent Gobillon, François-Charles Wolff, Patrice Guillotreau

The effect of buyers and sellers on fish market prices

Laurent Gobillon[*], **François-Charles Wolff**[**], **Patrice Guillotreau**[***]

April 2015

Abstract

Hedonic price regressions have become a standard tool to study how prices of commodity goods are related to quality attributes. In this paper, we extend the traditional price specification to take into account the unobserved heterogeneity of sellers, buyers and seller-buyer matches. The extended price specification is estimated on a unique exhaustive 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. Using data analysis techniques, fish and crustacean species are then sorted into groups depending on the respective importance of quality-related attributes and the different kinds of unobserved heterogeneity. The composition of these groups can be characterized in terms of production costs, consumers' willingness to pay and downstream markets of wholesalers.

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

JEL Classification: L11, Q22

[*] INED, 133 Boulevard Davout, 75980 Paris Cedex 20, France, PSE, CEPR and IZA. E-mail: laurent.gobillon@ined.fr http://laurent.gobillon.free.fr/

[**] Corresponding author. LEMNA, Université de Nantes, BP 52231, Chemin de la Censive du Tertre, 44322 Nantes Cedex, France and INED, Paris, France. E-mail: francois.wolff@univ-nantes.fr

[***] LEMNA and FR CNRS 3473-IUML, Université de Nantes, BP 52231, Chemin de la Censive du Tertre, 44322 Nantes Cedex, France. E-mail : patrice.guillotreau@univ-nantes.fr

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 attributes and the unit price of a good is fixed 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. Estimations are usually conducted on cross-section data using Ordinary Least Squares.

A limit of the traditional hedonic approach is that it does not take into account the unobserved heterogeneity of agents. Goods with specific attributes may be sold by sellers with specific marginal costs or bought only by buyers with specific tastes. Seller-buyer pairs may also matter since the information on the unobserved quality of goods sold by some sellers may be known only by some buyers. The measured effect of observable quality attributes on the price of goods can change when unobserved heterogeneity is taken into account.

The main contribution of our paper is to study the role of the unobserved heterogeneity of sellers, buyers, and seller-buyer matches in price setting using hedonic price regressions. Our application is on a unique exhaustive dataset of around 15 million transactions on the French wholesale fish auction market over the 2002-2007 period. However, it can be used to study the prices of any product whether it is raw food, transformed food or even a manufactured good as long as panel data are available, sellers and buyers' identity can be tracked across time, and there are repeated transactions involving the same economic agents.

Our approach borrows tools from 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, 2011; Sørensen and Vejlin, 2013). In our paper, we use a similar approach for fish prices per kilo 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, at best, 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, 2007; Asche and Guillen, 2012), to analyze retail prices in shops to assess the importance of packaging, brand or ecolabelling (Roheim, Gardiner and Asche, 2007; Roheim, Asche and Insignares, 2011), and to assess the validity of the law of one price (Gobillon and Wolff, 2015).[1] Contrary to previous studies on fish prices which usually focus on one single species or one single fish market, we provide results for most fish species based on estimations on transactions occurring on all French fish markets.

More precisely, we report regression results without and with unobserved heterogeneity for most fish and crustacean species with a significant market share. We also propose a way to classify species by the extent to which fish characteristics and unobserved heterogeneity among sellers, buyers and seller-buyer matches, contribute to explaining fish price variations. Our results show that, for most species, while fish characteristics remain the main determinant of fish prices, heterogeneity among sellers, buyers and matches also contributes to explaining prices. The role of matches remains nonetheless modest. Interestingly, the inclusion of unobserved heterogeneity in the analysis affects the marginal effect of fish characteristics on prices for several species. This suggests that unobserved heterogeneity terms should be included in regressions as controls to avoid biased estimates of the effect of observable fish attributes.

Data analysis techniques are used to classify fish and crustacean species into four groups. One group comprises high-quality species for which quality attributes play an important role because fish are highly differentiated with respect to their characteristics. A second group includes low-quality species for which there is a sizable explanatory power of buyer effects because wholesalers differ in their willingness to pay since they do not serve the same downstream markets. The third group is characterized by an important role of time effects because fish supply and consumers' willingness to pay vary seasonally. Finally, the fourth group consists in species for which the unobserved heterogeneity of agents and matches matters due to variability in production costs, willingness to pay and specific pairing for serving downstream markets.

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

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

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 suppose that it depends on the characteristics of the fish lot X_i composed of dummies related to size, presentation and quality. The standard hedonic specification is given by:

$$P_i = X_i\beta + \vartheta_t + \epsilon_i \quad (1)$$

where β is a vector of parameters, ϑ_t is a time fixed effect, and ϵ_i is a random error term. This specification is usually estimated with Ordinary Least Squares.

It is possible to add seller unobserved effects γ_j and buyer unobserved effects δ_k to this specification. In our setting where fish is sold at auctions, seller effects capture all the differences in fish quality across vessels that are not captured by variables in our dataset. An advantage of seller unobserved effects is that they capture the effect of all the vessel characteristics without the risk of being non-exhaustive. Similarly, buyer effects capture all the differences in willingness to pay that can affect prices, as buyers needing fish with specific characteristics are expected to make higher bids for it at auctions. As we will see below when describing the data, buyers cannot be tracked across fish markets.[2] Hence, unspecified buyer effects cannot be identified separately from market effects. The specification becomes:

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

where $j(i)$ is the seller involved in transaction i, $k(i)$ is the buyer and $t(i)$ is the month at which the transaction occurs. 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 frozen fish in large quantities after several weeks at sea. In the same way, fish traders supplying restaurants will seek to buy high-quality fish, while traders supplying hypermarkets will purchase a broader range of fish species at lower prices.

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 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

[2] Indeed, 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.

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.

Next, we introduce in equation (2) the effect of a match between seller j and buyer k, denoted θ_{jk}, as specific matches can influence fish prices. Indeed, specific vessels sell fish lots of higher quality and this quality is known only by a few customers through bilateral relationships. These customers agree to pay a higher price for the fish lots at auctions. More generally, match effects capture the price premium that some buyers agree to pay to some specific sellers. 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.[3] This fixed effect is decomposed in equation (3b) into the seller fixed effect, the buyer fixed effect and the match effect. The identification of the model is extensively discussed in Woodcock (2008, 2011). 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.

Our most general specification given by (3a) and (3b) is used to perform a variance decomposition 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 $V(X_i\hat{\beta})/V(P_{ijkt})$.

As a final step, we use these variance ratios to construct groups of species which are similar with respect to their price determinants. We first conduct a Principal Component Analysis (PCA) based on the five variance ratios of fish characteristics, time, seller, buyer and match effects, to assess the dimensions in which species can be distinguished.[4] The idea of the approach is to decrease the number of dimensions in which species are represented from five to a lower number by projecting species on a space of dimension lower than five such that distances between species are only slightly

[3] 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.

[4] As the five variance ratios do not have the same dispersion, we follow the common practice of dividing them by their standard deviation so that they have a comparable influence in the determination of axes when conducting the principal component analysis.

altered by projection. The selected subspace is such that the mean squared distance between projections is as high as possible or, put differently, such that the inertia of the projected cloud of species is maximized.

In fact, it is possible to show that the entire space can be decomposed into axes such that the first one maximizes the inertia of the projection among subspaces of dimension one, the second one maximizes the remaining inertia, and so on (see Jolliffe, 2010). As a result, axes explain a decreasing proportion of the total inertia of the cloud of species. In our application, we will focus on the two first axes as they explain most of the inertia of the cloud of species and thus contain most of the information contained in variance ratios which serves to differentiate species.

We then use an Ascendant Classical Hierarchy (ACH) based on these two first axes to construct groups of similar species. The groups are constructed by consecutive aggregation of subgroups containing one or more species using the Ward distance. The aggregation procedure involves aggregating the two subgroups at each step such that the loss of between-group inertia is minimized, and then repeating the operation until there are only a few subgroups left, and these are our selected groups. In practice, we stop the iterative procedure when four groups are left, as any further reduction in the number of groups leads to a significant loss of between-group inertia.

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 at 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 less than 10% of domestic demand which mostly depends on imports. Fish is traded in markets between vessels and buyers, mostly at auctions in trading rooms, using a mobile electronic auction clock or by internet (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 kilo. 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 fish market. A limitation of our data is that it is not possible to identify whether several accounts are owned by the same agent.[5]

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 over 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 includes more than 99.6% of transactions for 42 species and the minimum is as high as 95.1%. Contributions of species to total market value are reported in Figure A1 of the Online Appendix. It shows that trade is concentrated on a limited number of species. The two main species, sole and monkfish, represent 26.9% of total market value. The first five species represent 44.2% of this value and the first ten species 66.7%.

Table 1 shows that there is considerable heterogeneity in the average price per kilo. The most expensive species is lobster, with a price per kilo around 21 euros. There are several very cheap species, such as whiting or mackerel, with a price per kilo 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 with a significant market share, there are around 3,200 vessels selling to 3,000 buyers for sole, but only 400 vessels selling to 1,000 buyers for Norway lobster (live). The correlation between numbers of buyers and sellers is 0.88. 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

[5] 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.

matches for sole, but only 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

Coefficient estimates

In Table 3, we report results of hedonic price regressions for the two species which have by far the highest market shares, sole and monkfish. Estimation results are given for three specifications: one without unobserved heterogeneity (equation 1), one including additive seller and buyer fixed effects (equation 2), and one including seller-buyer fixed effects (equation 3a).

[Insert Table 3]

In Panel A for sole, column 1 corresponds to the Ordinary Least Squares estimates when fish characteristics and month dummies are introduced.[6] The R^2 is 0.481, meaning that observable fish characteristics and time explain as much as 48.1% of price variations. The coefficients of fish characteristics have the expected sign. 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% less expensive.[7] Results are consistent with medium-sized fish being the most valued. Presentation significantly influences price per kilo. Low-quality fish (grade B) is 45.6% cheaper than extra-quality fish (grade E). Gutted fish is 7.9% more expensive than whole fish because non-edible parts have been eliminated. Month-year effects are represented in Figure B1 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.

[6] 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 sole, for instance, the R^2 increases only at the margin from 0.4814 to 0.4818 when adding fish quantity to the set of explanatory variables.

[7] 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.

We then estimate a specification where both seller and buyer fixed effects have been added. Results reported in column (2) of panel A show a significant improvement of the fit, with an increase of the R^2 from 0.481 to 0.614. This suggests some heterogeneity among 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.

Finally, we consider a hedonic price specification with seller-buyer fixed effects. Results reported in column 3 show that the fit improves again, with the R^2 increasing from 0.614 to 0.659. 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.[8] 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.[9]

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 B2 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 0.582 to 0.693 (column 2). Introducing seller-buyer fixed effects instead of seller and buyer fixed effects increases the R^2 to 0.734 (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% more expensive when seller and buyer fixed effects are added.

We estimate hedonic price regressions for every species to obtain systematic conclusions about the importance of unobserved heterogeneity in explaining variations in fish prices.[10] Interestingly, the introduction of unobserved heterogeneity changes the effect of some fish characteristics in a sizable way for several species. For cuttlefish in particular, whereas low quality fish (grade B) is 30.0% less expensive than extra quality fish (grade E) when unobserved heterogeneity terms are omitted, it is only 10.8% less expensive when seller and buyer fixed effects are introduced. There is a similar pattern for hake, the respective figures being 50.5% and 38.6%. For cod, whereas fillets are 63.7% more expensive than whole fish when unobserved heterogeneity terms are omitted, they are only 18.3% more expensive when seller and buyer fixed effects are introduced. For Norway lobster

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

[9] 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.

[10] Results for all other species are reported in part B of the Online Appendix.

(frozen), it is the opposite with pieces being 53.2% less expensive than whole lobster when unobserved heterogeneity is omitted, but only 37.6% less expensive when seller and buyer fixed effects are introduced into the regression.

Differences can be explained by some unobserved heterogeneity among sellers correlated both with the presentation category and unobserved fish quality, as vessels use different types of fishing gear. They can also 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 wholesalers, multiple grocers or mongers, and different downstream markets where buyers resell fish.

Price variations explained by fish characteristics and unobserved heterogeneity terms

We also evaluate the explanatory power of unobserved heterogeneity terms for every species. Figure 2 reports, for each 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 the mackerel, but it reaches 0.70 for Norway lobster (frozen).

[Insert Figure 2]

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 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

Explanatory power of fish, seller, buyer and match effects

Another way to assess the importance of the different terms 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.[11] Table 4 reports, for each term, the ratio between the variance of its effect and the variance of fish price.[12] The higher the variance ratio of an effect, the higher the explanatory power of the related term.

[11] Match effects are obtained by further estimating equation (3b), as explained in Appendix A.

[12] Note that ratios in Table 4 do not sum to 1. This is because the covariances between the different types of effects are not equal to zero. The values of covariances are available upon request.

[Insert Table 4]

As expected, the explanatory power of fish characteristics is high, as the average variance ratio for fish characteristics is 31.9%. There are large variations across species: this ratio is only 7.9% for squid, but 61.1% for Norway lobster (frozen). Time fixed effects have a lower explanatory power, but it is still significant as the related average variance ratio is 10.4%. This ratio is very large for some specific species with seasonal demand. For instance, the ratio is 33.2% for lobster, which is consumed in large quantities in summer and in December, but less during the rest of the year.

Overall, unobserved heterogeneity has a high explanatory power for many species, the average variance ratio for the sum of all the unobserved heterogeneity terms being 29.2%. Buyer heterogeneity is the main unobserved term affecting prices. In particular, the variance ratio of buyer effects is larger than that of seller effects for all species, and it is larger than that of match effects for all species except one. The average variance ratio of buyer effects is 20.7%. The ratio is low for cuckoo ray and seabass (line-caught), at 4.2% and 5.2%, respectively, but very high for cuttlefish, at 43.6%. By contrast, the average variance ratio of seller effects is only 5.2%. It is very low for some species such as Norway lobster (live) for which it is only 1.5%, but it is quite high for other species such as crab and octopus, at 14.6% and 15.2%, respectively. Finally, the average variance ratio of match effects is 6.2%, with some variations across species. It is quite low for Norway lobster (frozen) at 2.1%, but reaches 10.6% for ling.

Robustness check

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. As a robustness check, we replicated our analysis considering only transactions for matches with at least 2, 5 or 10 transactions, as this should alleviate identification problems at the expense of making a non-random selection on transactions.[13] We find that the explanatory power of matches is smaller, but otherwise conclusions remain qualitatively similar.

4.3. A classification of fish and crustacean species

As a last step in our analysis, we attempt to construct groups of fish and crustacean species which are similar with respect to their price determinants. We first conduct a principal component analysis to

[13] Detailed results are reported in part C of the Online Appendix.

identify the dimensions in which fish and crustaceans differ. We use five variables, which are the variance ratios of fish characteristics, time effects, seller effects, buyer effects and match effects, and whose values are reported in Table 4.[14]

Results are summarized in Table 5 and the two main axes of the principal component analysis are represented in Figure 3.[15] The first axis is by far the main dimension in which species differ, as it explains 46% of the inertia of the cloud of species. It opposes fish characteristics to the unobservables related to sellers, buyers and matches. This opposition is driven by the large negative correlations between the effects of fish characteristics and match effects (-0.68), seller effects (-0.43) and buyer effects (-0.43). The second axis has less importance, explaining less than 23% of the inertia of the cloud of species. It mostly opposes time effects and buyer effects, the correlation between these two types of effects being equal to -0.17.

[Insert Table 5 here]

[Insert Figure 3 here]

We then use the positions of species on the first two axes in an ascendant classical hierarchy to construct groups of species with similar price determinants. We consider a classification with four groups which are represented in Figure 4.[16] Most species in the first group have negative values on the first axis and fish characteristics usually have a large explanatory power. The variance ratio of fish characteristics is 44.6% on average in this group, compared to 32.4% for the whole sample of species. Unobserved heterogeneity does not play much of a role for most species in this group. The average variance ratios of seller, buyer and match effects are all below the averages computed for the whole sample of species. In particular, the group contains sole, monkfish, Norway lobster (live or frozen), seabass (line-caught), turbot and haddock. Most species are expensive (around 10€/kg) and highly differentiated across presentation categories, consistent with an important role of fish characteristics in price setting. For instance, Norway lobsters are less valued when frozen rather than alive, except the largest ones, monkfish is more valued whole rather than beheaded, and portion-size soles (size 2) are the most appreciated.

[Insert Figure 4 here]

Most species in the second group have negative values on the second axis. Time effects usually have a low explanatory power and buyer effects have an explanatory power slightly above average. As shown in Table 6, the average variance ratios of time and buyer effects are respectively 5.6% and 22.2%, compared to 10.5% and 19.3% for the whole sample of species. This group includes hake,

[14] Horse mackerel is excluded from the analysis because it looks like an outlier (its variance ratio of buyer effects is very high, at 83.7%) and the market share of this species is very low.

[15] Appendix C reports the coordinates of species on the two first axes, as well as their contributions and some projection information.

[16] This is the number of classes below ten where the Calinski/Harabasz Pseudo-R^2 has a local maximum.

cuttlefish, John Dory, cod, ray, plaice and conger eels. These species have a low price (around 4€ per kilo) which is not subject to seasonal variability as fish is caught the whole year and is purchased mostly by wholesalers. Willingness to pay differs among buyers depending on their downstream markets. Indeed, marketing efforts (such as discounted prices and advertising) are sometimes considerable as these species are of low value and the profits buyers can derive from sales vary across downstream customers.

[Insert Table 6 here]

Nearly all species in the third group have positive values on both the first and second axis, and are characterized by a large explanatory power of time effects and a slightly below average explanatory power of seller and match effects. In particular, time effects have an average variance ratio of 18.3% compared to 10.5% for the whole sample of species. This group includes lobster, squid, red mullet, seabass (non-line caught), pollack and ling. With the noticeable exception of lobster which is caught in traps, all these species sell at around 7€ per kilo and are caught seasonally by pelagic trawlers. For lobster, consumers' willingness to pay varies seasonally and is highest during summer and the Christmas holidays.

Finally, the fourth group is characterized by a high explanatory power of buyer, seller and match effects. The variance ratios of these three types of effects are respectively 30.0%, 9.1% and 8.3%, compared to 19.3%, 5.0% and 6.2% for the whole sample of species (see Table 6). The only species in that group with a significant market share is mackerel. This low-value species is mainly harvested in the English Channel by trawlers and sold to wholesalers who export it frozen or canned to foreign markets where it is sold at rather cheap prices. It is also caught by small-scale vessels (such as purse-seiners, gill-netters or liners) and sold to wholesalers who resell it on retail markets for higher prices. This may explain the high variance ratios of the three unobserved heterogeneity terms, as large trawlers and small-scale vessels differ in their production costs, sellers differ in their willingness to pay depending on how products are presented on the downstream markets, and there can be specific matches depending on the segment of the downstream market involved.

5. Conclusion

In this paper, we have shown how the unobserved heterogeneity of sellers, buyers as well as matches between sellers and buyers can be simultaneously taken into account in hedonic price regressions. 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 work contrasts with the literature, as the typical study usually focuses on one single species or one single fish market, and regresses fish prices on a set of observable characteristics related to fish quality without taking the unobserved heterogeneity into account.

When unobserved heterogeneity terms are included in hedonic price regressions, the effects of quality-related fish characteristics change significantly for some species. For almost all species, observable fish characteristics are found to have the largest explanatory power, but the explanatory power of seller, buyer and match effects is also significant. We finally propose a classification of fish and crustacean species depending on the explanatory power of observables and unobservables using a principal component analysis followed by an ascendant classical hierarchy. This classification tends to differentiate species by their value, seasonality and downstream markets.

Future research could study how buyers sort across sellers, and how prices evolve over time for matches between sellers and buyers as buyers acquire information on the unobserved quality provided by sellers through repeated transactions.

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.

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

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

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., (2015), “Evaluating the law of one price using micro panel data: The case of the French fish market”, *American Journal of Agricultural Economics*, forthcoming.

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

Jolliffe I. (2010), *Principal Component Analysis*, 2nd edition, Springer-Verlag, New York, 487p.

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.

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

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

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.

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.

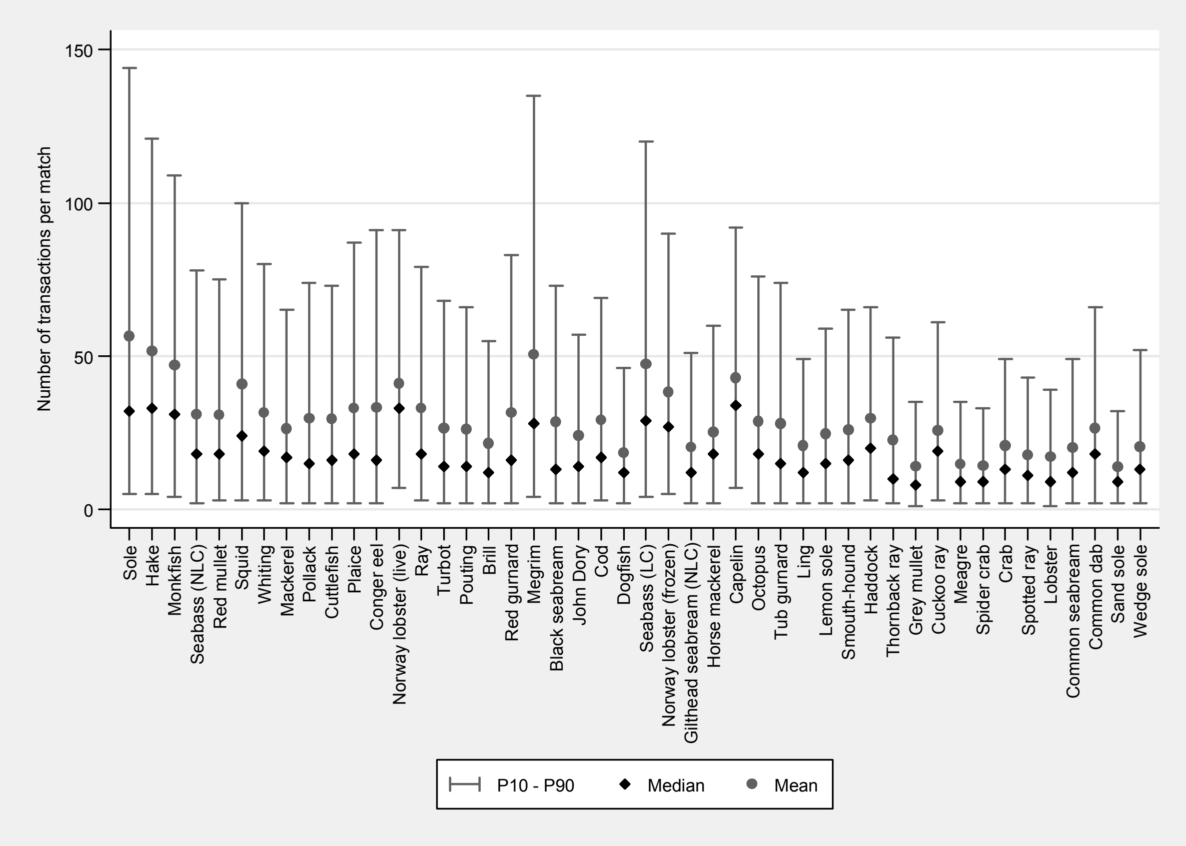
Sørensen T., Vejlin R., (2013), “The importance of worker, firm and match effects in the formation of wages”, *Empirical Economics*, vol. 45, pp. 435-464.

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.

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

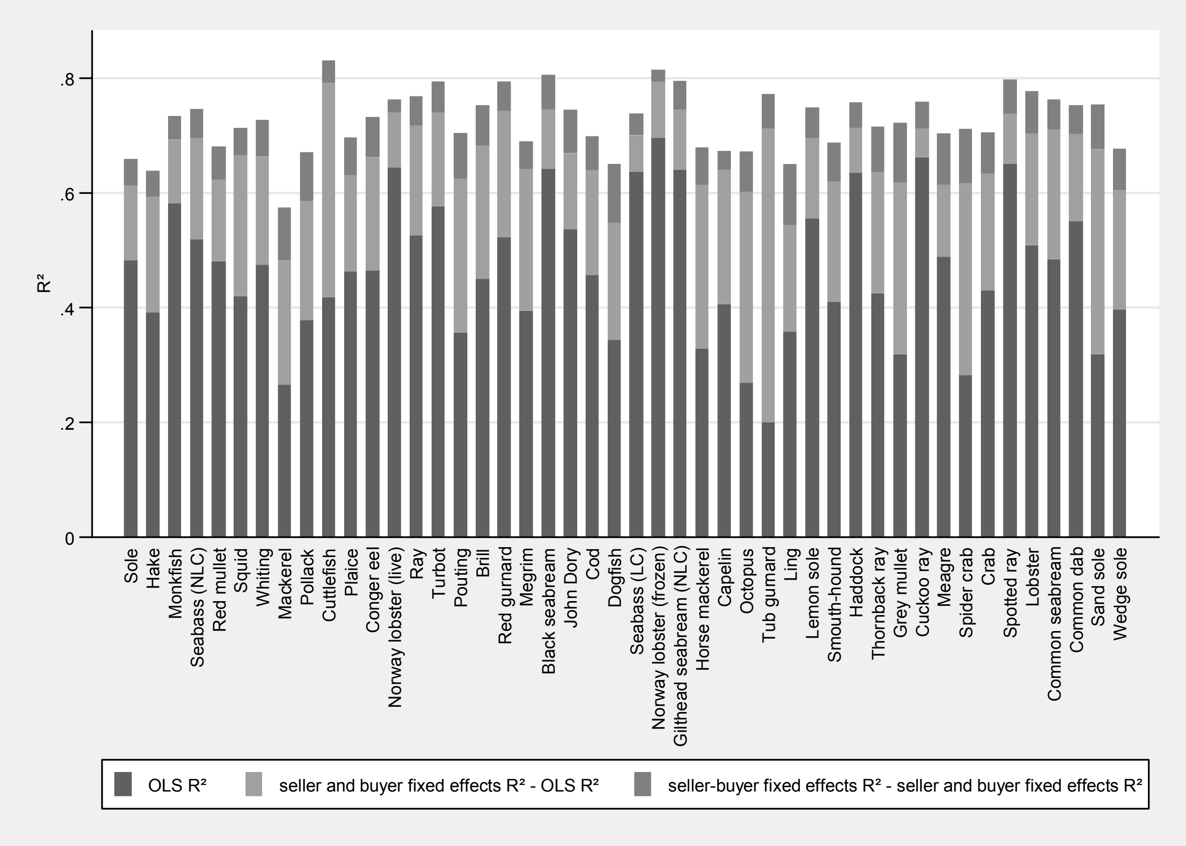
Woodcock S.D., (2011), “Match effects”, *mimeo*, Department of Economics, Simon Fraser University.

Figure 1. Number of transactions per match



Source: RIC 2002-2007, authors' calculations.
Note: NLC = not line-caught, LC = line-caught.

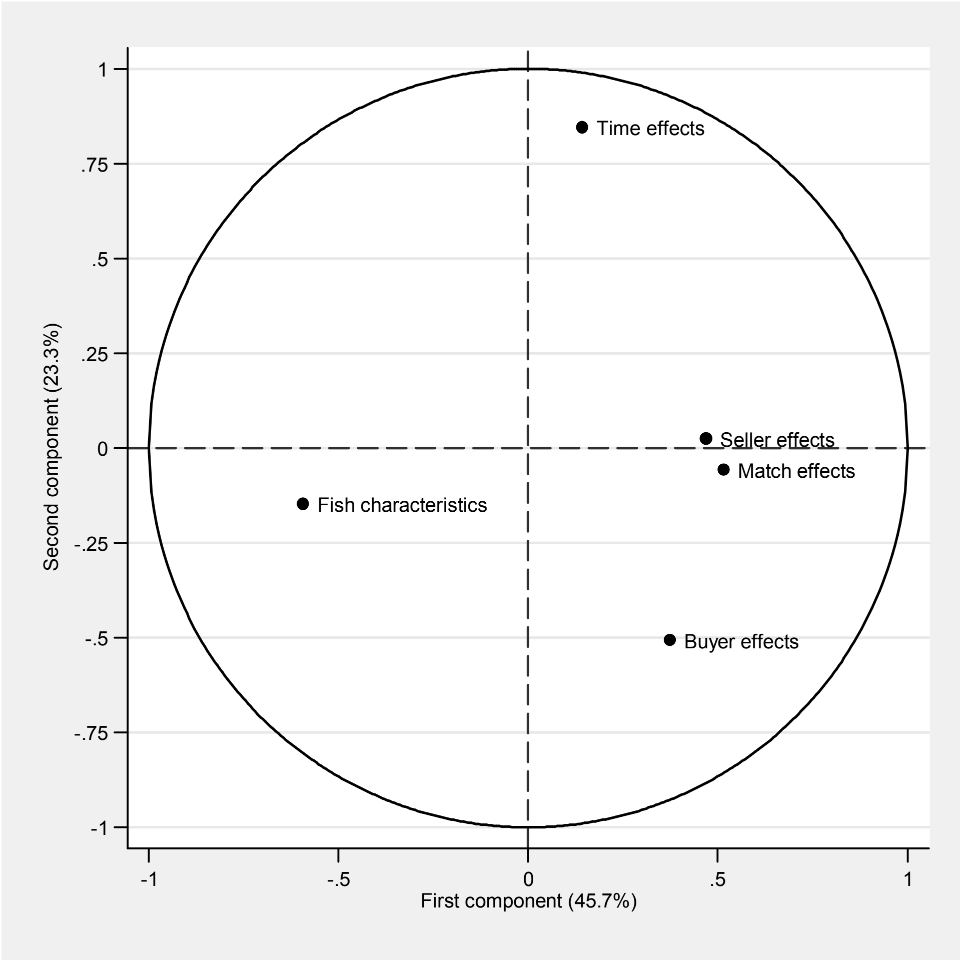
Figure 2. Differences in model goodness of fit



Source: RIC 2002-2007, authors' calculations.

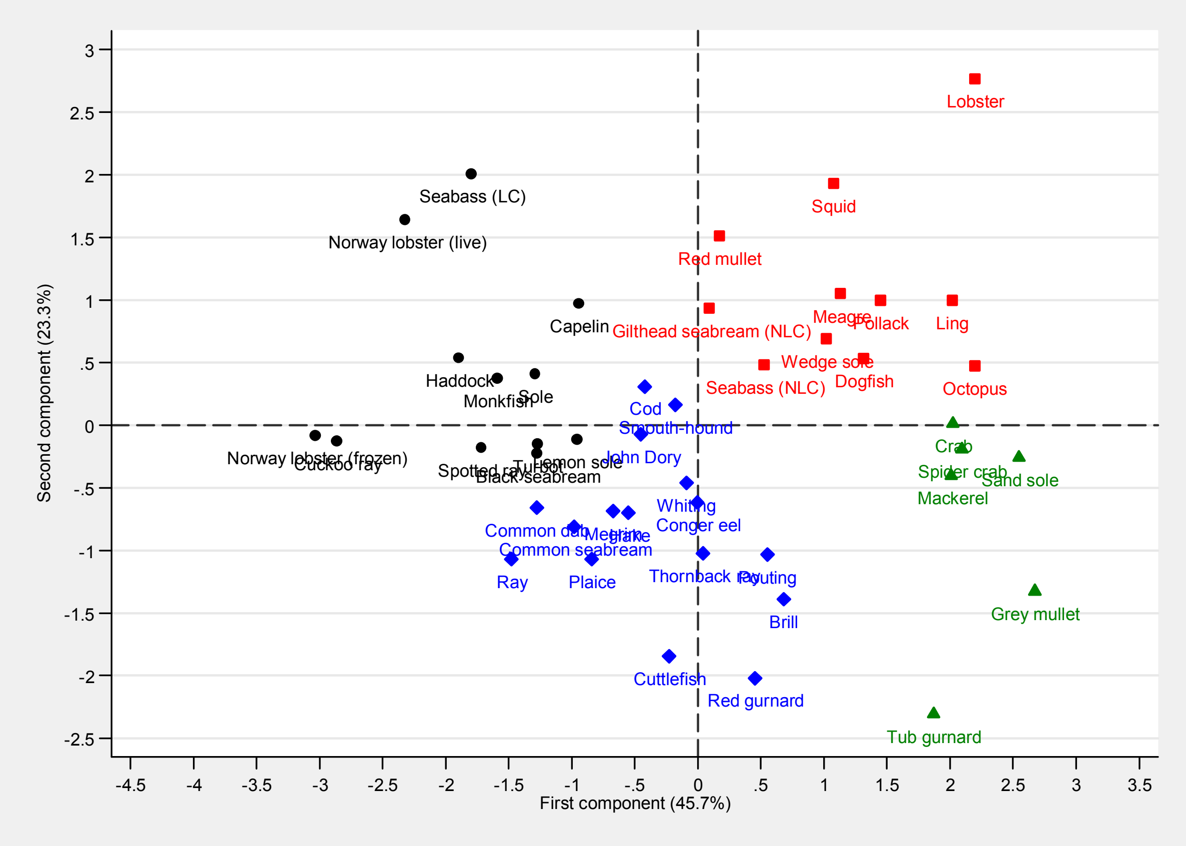
Note: NLC = not line-caught, LC = line-caught. "OLS R^2" gives the R-square of a specification without any unobserved heterogeneity terms related to sellers and buyers, which is estimated with OLS. "seller and buyer fixed effects R^2" gives the R-square of a specification additionally including seller and buyer fixed effects. "seller-buyer fixed effects R^2" gives the R-square of a specification including seller-buyer fixed effects, but not seller and buyer fixed effects.

Figure 3. Principal component analysis of variance decomposition of fish prices



Source: RIC 2002-2007, authors’ calculations.

Figure 4. Classification of fish and crustacean species obtained from the Ascendant Classical Hierarchy



Source: RIC 2002-2007, authors' calculations.

Note: group 1 is represented by black dots, group 2 by blue diamonds, group 3 by red squares and group 4 by green triangles.

Table 1. Descriptive statistics on transactions by species

Fish species	Price per kilo (in euros)		Number of transactions
	Average	St. dev.	
Sole	12.65	4.61	1,457,282
Hake	5.19	2.37	1,206,817
Monkfish	5.79	2.44	863,500
Seabass (NLC)	10.55	4.92	705,547
Red mullet	7.08	3.89	690,916
Squid	7.37	3.75	549,083
Whiting	2.38	1.48	526,094
Mackerel	1.52	1.12	466,378
Pollack	4.36	2.08	466,037
Cuttlefish	2.99	2.41	423,015
Plaice	1.47	0.78	352,040
Conger eel	2.20	1.39	349,239
Norway lobster (live)	11.03	4.74	348,816
Ray	2.89	1.42	347,955
Turbot	14.67	5.78	338,921
Pouting	0.86	0.67	335,741
Brill	9.86	3.91	319,475
Red gurnard	1.76	1.88	310,892
Megrim	4.60	2.49	290,904
Black seabream	3.36	2.30	280,202
John Dory	9.34	3.91	278,069
Cod	4.13	1.66	260,137
Dogfish	0.62	0.45	248,799
Seabass (LC)	14.55	3.98	239,293
Norway lobster (frozen)	9.43	4.79	215,206
Gilthead seabream (NLC)	9.78	5.84	185,221
Horse mackerel	0.95	0.73	181,585
Capelin	1.56	0.87	180,664
Octopus	3.15	2.01	177,485
Tub gurnard	2.85	3.24	176,692
Ling	2.69	0.91	175,774
Lemon sole	4.44	2.22	161,666
Smouth-hound	1.39	0.80	158,639
Haddock	1.80	0.86	154,963
Thornback ray	3.17	1.52	138,070
Grey mullet	1.51	1.12	133,904
Cuckoo ray	1.80	0.85	111,493
Meagre	4.71	3.16	109,290
Spider crab	2.00	1.15	102,430
Crab	2.59	1.31	101,098
Spotted ray	3.03	1.20	92,074
Lobster	20.89	6.75	86,372
Common seabream	7.38	5.96	73,041
Common dab	1.18	0.87	67,961
Sand sole	6.06	2.65	65,692
Wedge sole	5.58	2.22	60,286

Source: RIC 2002-2007, authors' calculations.
Note: NLC = not line-caught, LC = line-caught.

Table 2. Descriptive statistics of the market

Fish species	Number of vessels	Average number of vessels per account	Number of accounts	Average number of accounts per seller	Number of matches
Sole	3216	40.26	3023	42.83	129,482
Hake	2254	44.08	2745	36.19	99,348
Monkfish	2339	34.72	2786	29.15	81,208
Seabass (NLC)	3543	29.63	2986	35.15	104,971
Red mullet	2768	34.11	2884	32.73	94,403
Squid	2195	29.88	2787	23.53	65,587
Whiting	2444	30.55	2237	33.38	74,671
Mackerel	2553	27.96	2895	24.66	71,383
Pollack	2695	28.61	2153	35.81	77,092
Cuttlefish	3108	22.33	2672	25.97	69,389
Plaice	3334	17.16	2433	23.51	57,205
Conger eel	2432	23.72	2042	28.25	57,681
Norway lobster (live)	390	65.22	959	26.52	25,437
Ray	2576	19.96	1996	25.76	51,423
Turbot	2898	20.62	2476	24.13	59,753
Pouting	2477	23.26	2013	28.62	57,621
Brill	2742	22.74	2553	24.42	62,352
Red gurnard	2340	21.84	2606	19.61	51,107
Megrim	1007	30.48	1948	15.76	30,694
Black seabream	2462	21.77	2135	25.11	53,610
John Dory	2178	22.69	2418	20.44	49,413
Cod	1780	21.00	1642	22.76	37,376
Dogfish	2753	17.80	2119	23.13	49,012
Seabass (LC)	1186	22.23	1464	18.01	26,361
Norway lobster (frozen)	489	40.03	962	20.35	19,577
Gilthead seabream (NLC)	1902	19.29	1916	19.15	36,699
Horse mackerel	1845	15.33	1999	14.15	28,278
Capelin	210	61.25	705	18.24	12,862
Octopus	1726	15.36	1638	16.19	26,513
Tub gurnard	1894	17.29	1854	17.66	32,747
Ling	1723	19.45	1668	20.09	33,517
Lemon sole	1361	20.21	1599	17.20	27,510
Smouth-hound	2114	12.10	1149	22.27	25,587
Haddock	810	24.01	1163	16.72	19,449
Thornback ray	1692	17.47	1153	25.64	29,563
Grey mullet	2419	14.78	2134	16.75	35,749
Cuckoo ray	847	18.87	762	20.97	15,981
Meagre	1039	22.37	667	34.84	23,238
Spider crab	1304	18.17	1294	18.31	23,699
Crab	1116	17.08	1418	13.44	19,061
Spotted ray	1069	17.81	827	23.02	19,037
Lobster	1453	14.04	1684	12.11	20,394
Common seabream	343	37.09	659	19.30	12,721
Common dab	768	13.45	511	20.21	10,328
Sand sole	1213	12.48	858	17.64	15,138
Wedge sole	446	23.30	461	22.54	10,392

Source: RIC 2002-2007, authors' calculations.
Note: NLC = not line-caught, LC = line-caught.

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)		(0.001)	(0.001)	(0.001)
	3	-0.075***	-0.067***	-0.065***
		(0.001)	(0.001)	(0.001)
	4	-0.193***	-0.197***	-0.195***
		(0.001)	(0.001)	(0.001)
	5 (small)	-0.515***	-0.537***	-0.536***
		(0.001)	(0.001)	(0.001)
Presentation	Gutted	0.076***	0.012***	0.009***
(ref: Whole)		(0.000)	(0.002)	(0.002)
Quality	A	-0.135***	-0.062***	-0.058***
(ref: Extra)		(0.001)	(0.001)	(0.001)
	B (low)	-0.680***	-0.579***	-0.582***
		(0.002)	(0.002)	(0.002)
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)		(0.001)	(0.001)	(0.001)
	3	-0.045***	-0.072***	-0.073***
		(0.001)	(0.001)	(0.001)
	4	-0.112***	-0.134***	-0.133***
		(0.001)	(0.001)	(0.001)
	5 (small)	-0.365***	-0.365***	-0.360***
		(0.001)	(0.001)	(0.001)
Presentation	Gutted	-0.048***	0.150***	0.155***
(ref: Whole)		(0.001)	(0.002)	(0.002)
	Gutted head-off	0.546***	0.711***	0.691***
		(0.003)	(0.004)	(0.004)
	Gutted head-off, peeled	0.726***	1.003***	0.985***
		(0.003)	(0.016)	(0.020)
	Pieces	0.743***	0.834***	0.824***
		(0.002)	(0.003)	(0.003)
Quality	A	-0.090***	-0.018***	-0.020***
(ref: Extra)		(0.001)	(0.001)	(0.002)
	B (low)	-0.608***	-0.517***	-0.508***
		(0.002)	(0.002)	(0.002)
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 are in parentheses; ***: significant at 1%, **: significant at 5%, *: significant at 10%.

Table 4. Variance decomposition of fish prices, by species

Fish species	Variance of price	Fish characte-ristics	Time	Unobserved heterogeneity				Residual
				All	Sellers	Buyers	Match	
Sole	0.163	36.1%	10.5%	19.3%	2.2%	11.6%	4.5%	34.1%
Hake	0.220	41.0%	5.9%	28.5%	6.9%	21.0%	4.6%	36.2%
Monkfish	0.154	40.0%	9.9%	18.3%	2.4%	10.4%	4.1%	26.6%
Seabass (NLC)	0.202	22.4%	15.6%	26.6%	5.1%	24.7%	5.1%	25.4%
Red mullet	0.490	25.0%	18.2%	20.8%	6.0%	11.0%	5.7%	31.9%
Squid	0.213	7.9%	24.0%	35.5%	5.0%	20.3%	4.8%	28.6%
Whiting	0.506	32.2%	4.9%	27.4%	5.8%	15.2%	6.5%	27.3%
Mackerel	0.654	14.7%	7.8%	33.0%	7.4%	22.9%	9.3%	42.6%
Pollack	0.252	18.1%	14.7%	30.5%	8.0%	12.7%	8.4%	32.9%
Cuttlefish	0.467	35.7%	6.4%	50.7%	2.0%	43.6%	3.9%	16.9%
Plaice	0.426	42.4%	2.2%	26.6%	3.3%	17.8%	6.5%	30.4%
Conger eel	0.429	29.9%	5.5%	28.5%	3.4%	19.2%	7.0%	26.7%
Norway lobster (live)	0.178	48.0%	20.8%	12.9%	1.5%	11.0%	2.2%	23.8%
Ray	0.359	48.7%	3.0%	26.1%	2.9%	18.8%	5.0%	23.1%
Turbot	0.175	40.9%	7.7%	23.2%	2.1%	14.1%	5.3%	20.6%
Pouting	0.573	26.8%	3.7%	36.4%	3.9%	23.0%	7.9%	29.5%
Brill	0.194	24.2%	3.4%	38.6%	3.7%	29.7%	7.0%	24.7%
Red gurnard	0.830	45.3%	1.4%	27.9%	11.5%	34.4%	5.1%	20.5%
Megrim	0.405	32.0%	6.3%	30.5%	2.2%	22.8%	4.7%	31.0%
Black seabream	0.711	43.9%	5.7%	19.2%	3.5%	10.3%	5.9%	19.4%
John Dory	0.261	37.0%	8.1%	22.5%	2.7%	13.3%	7.6%	25.5%
Cod	0.184	32.3%	10.5%	25.6%	4.1%	13.8%	5.9%	30.1%
Dogfish	0.354	23.8%	15.7%	31.9%	3.2%	20.7%	10.2%	35.0%
Seabass (LC)	0.089	41.7%	21.0%	10.9%	1.9%	5.2%	3.8%	26.2%
Norway lobster (frozen)	0.275	61.1%	7.8%	15.0%	2.8%	10.6%	2.1%	18.5%
Gilthead seabream (NLC)	0.602	41.0%	17.1%	15.9%	10.5%	16.8%	5.0%	20.5%
Horse mackerel	0.574	10.5%	4.5%	53.0%	17.2%	83.7%	6.4%	32.1%
Capelin	0.388	36.0%	21.8%	30.5%	0.7%	27.3%	3.1%	32.7%
Octopus	0.470	26.9%	15.8%	41.8%	15.2%	24.5%	7.1%	32.8%
Tub gurnard	1.167	11.4%	2.0%	66.6%	5.3%	46.6%	5.9%	22.8%
Ling	0.134	11.3%	16.4%	32.6%	4.7%	16.3%	10.6%	34.9%
Lemon sole	0.363	34.5%	7.1%	21.7%	2.4%	13.4%	5.4%	25.1%
Smooth-hound	0.460	35.3%	12.1%	31.4%	3.5%	18.8%	6.8%	31.2%
Haddock	0.305	46.6%	11.1%	12.7%	2.3%	8.5%	4.4%	24.2%
Thornback ray	0.361	36.4%	3.9%	34.6%	4.0%	21.2%	7.8%	28.4%
Grey mullet	0.561	14.4%	5.2%	43.7%	7.5%	33.4%	10.3%	27.8%
Cuckoo ray	0.321	60.1%	5.1%	9.7%	1.7%	4.2%	4.5%	24.2%
Meagre	0.674	21.0%	14.2%	23.4%	6.8%	9.6%	8.9%	29.6%
Spider crab	0.405	21.1%	12.2%	45.7%	7.9%	27.5%	9.4%	28.8%
Crab	0.338	26.8%	11.7%	29.4%	14.6%	23.7%	7.1%	29.4%
Spotted ray	0.280	46.2%	4.5%	16.2%	2.6%	6.2%	5.8%	20.3%
Lobster	0.105	15.7%	33.2%	28.1%	8.5%	23.2%	7.5%	22.2%
Common seabream	0.921	48.4%	9.2%	32.5%	2.6%	28.0%	5.2%	23.7%
Common dab	0.512	40.4%	3.6%	21.5%	3.0%	14.5%	5.0%	24.7%
Sand sole	0.286	11.1%	9.3%	54.6%	11.7%	25.7%	7.8%	24.6%
Wedge sole	0.190	20.7%	16.2%	31.5%	5.0%	21.3%	7.3%	32.3%

Source: RIC 2002-2007, authors' calculations.

Note: NLC = not line-caught, LC = line-caught.

Table 5. Results of the principal component analysis

Variables	Component					Inertia	
	First	Second	Third	Fourth	Fifth	Axis	Proportion
Fish characteristics	-0.593	-0.148	0.055	0.383	0.690	1	0.457
Time effects	0.144	0.846	0.336	-0.146	0.359	2	0.233
Seller effects	0.469	0.024	0.198	0.856	-0.083	3	0.152
Buyer effects	0.375	-0.508	0.631	-0.305	0.333	4	0.127
Pure match effects	0.516	-0.058	-0.668	-0.076	0.527	5	0.032

Source: RIC 2002-2007, authors' calculations.

Note: the first five columns give the coordinates of variance ratios on the five axes determined by the principal component analysis. Column labeled "Axis" gives the rank of the axis and "Proportion" gives the proportion of inertia of the cloud of species explained by the axis.

Table 6. Average shares of price variances for each of the four groups determined by the ascendant classical hierarchy

Variables	Group 1	Group 2	Group 3	Group 4	All species
Fish characteristics	44.6%	36.7%	21.3%	16.6%	32.4%
Time effects	11.1%	5.6%	18.3%	8.0%	10.5%
Seller effects	2.2%	4.1%	7.1%	9.1%	5.0%
Buyer effects	11.1%	22.2%	18.3%	30.0%	19.3%
Match effects	4.2%	6.0%	7.3%	8.3%	6.2%

Source: RIC 2002-2007, authors' calculations.

Note: horse mackerel is excluded from the computation of the averages for all species as it is an outlier that is not taken into account in the analysis.

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 dummies 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 dummies 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 dummies to take into account the set of seller fixed effects.

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 allow 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.

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 dummies. The resulting equation can then be estimated using Ordinary Least Squares, but this procedure is not efficient as it does not take properly into 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}.[17]

[17] 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).

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).[18] Second, we delete observations corresponding to direct sales and restrict our attention to transactions at auctions (909,307 observations deleted).[19] 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 kilo 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).[20]

[18] There are missing identifiers only for buyers. The identifier is always given for vessels involved in transactions.
[19] We eliminated direct sales because the fish price for such transactions is fixed in a very different way.
[20] 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.