DOES BOAT ORDER IN THE AUCTION AFFECT THE PRICE IN FISH MARKETS?

HEDONIC PRICING FOR HAKE IN NORTHERN SPAIN

Antonio Álvarez
Department of Economics. University of Oviedo
Email: alvarez@uniovi.es
Phone: +34985104859
ORCID ID: https://orcid.org/0000-0001-7603-1047

ABSTRACT

This paper estimates a hedonic price function for hake using data from a fish auction market in Northern Spain. The model includes some variables that have not been previously considered in the literature, such as the number of boats present at the auction, the number of buyers, the number of yearly landings at this port by boats, the effect of holidays, and the order of the boat in the auction, which is the main variable of interest. Aside from confirming that well-known fish characteristics (size, freshness…) contribute to higher prices, the results show that boat order has a quadratic relationship with price, implying that there is an optimal order in the auction. Furthermore, the results also show that fishmongers pay higher prices than larger buyers, that boats that land more often at the port get a premium, and that lower prices are reached on the days before and after a holiday.

Key words: fish auctions, hedonic prices, boat order, panel data, hake, Spain.

JEL codes: Q22, D44, C23.

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INTRODUCTION

The price received by fishermen, that is, the ex-vessel price, is formed in wholesale fish markets, most usually through an auction process. When boats come to port, landings are auctioned, although it is also possible that some buyers have settled on a deal with a boat owner such that the buyer will take all the fish at a price set in advance. Notwithstanding, auctions are the principal system used to allocate landings to buyers (Guillotreau and Jiménez-Toribio 2011).

Fish price is a key variable used by boat skippers to select the port of landing. In most fishing ports, fish is auctioned after arrival. Therefore, the price received by fishers depends not only on the species caught and the quality of the fish but also on several other aspects related to market conditions such as number and type of buyers and/or the competition by other boats. It is important to note that some of these characteristics become decision variables for the fishermen and therefore the value of landings is not completely exogenous (Asche, Chen, and Smith 2015).

Given the concern about low fishermen revenues and the fact that the catch of most species is limited by quotas, the study of fish price formation becomes important to understand possible ways to improve fishermen income. However, the study of price formation in fish auction markets is not very common in the fisheries economics literature. Moreover, the use of econometric techniques to explain price formation in fisheries is rather recent (e.g., McConnell and Strand 2000; Sjöberg 2015; Gobillon, Wolff, and Guillotreau 2017).

The objective of this paper is to explain price variability across boats in one of the most important fish auction markets in Northern Spain, namely the fish market in the city of Avilés. For this purpose, we avail of a very rich dataset provided by the firm that runs an electronic daily auction at this port. The data include records at the bid level on the characteristics of the fish being auctioned, the boats, the buyers, and the market. The dataset comprises all transactions that took place in 2016.[1]

Our empirical analysis involves the estimation of a hedonic price model (Rosen 1974), where fish price is explained by a set of characteristics of the fish being auctioned as well as the conditions of the market. Our empirical model exploits a wealth of data which permits the use of a greater set of characteristics in the hedonic price function than previous papers, such as the number of boats and buyers present at the auction, the number of yearly landings at this port by boats, the effect of holidays, and the order of the boat in the auction, where the latter is our primary variable of interest.

The main contribution of this paper to the literature of fish price formation is to assess the role played by the order of the boats in the auction. Order is equivalent to the time of arrival at port. In most markets, the auction is carried out by boat, that is, the whole catch is auctioned together species by species (the usual order being 'first come, first auctioned'). If the order in the auction matters for the price received by boats, the time of landing at port therefore becomes a critical decision to be made by the skipper. To the best of our knowledge, this variable has not been previously considered in the fisheries literature.[2]

The order in which the boats are auctioned is an issue which has obviously been considered by auction managers, since fishers are aware that the price during the auction varies (often substantially). While auctioning by order of arrival at port is the prevailing system in most Spanish ports, some exceptions exist. For example, in some ports of the Mediterranean coast (such as Villajoyosa or Santa Pola) the fishermen's association establishes a random order at the beginning of the year which rolls daily. Thus, a boat which was auctioned today in first place will be auctioned tomorrow in second place, and so on. In this way, the effect of order is averaged out over the year. In Palamós (Catalonia) the inshore fleet

[1] The authors wish to thank the staff of Rula de Avilés S.A. not only for providing the data but also for their detailed and illuminating explanations about the functioning of the auction. Special thanks go to the General Manager, Ramón Álvarez, the Head of the Computing Department, Jesús Solla, and to the Chief Auctioneer, Jorge Fernández.

[2] Gallegati et al. (2011) and Salladarré et al. (2017) use a similar measure, the rank order of the transactions in a given period, i.e., they pool all the transactions carried in a particular order throughout the whole auction.

are auctioned randomly; the order being assigned every day before the auction starts. This system is also used to auction purse seiners in Avilés. So, while the importance of order is well known, its effect on price is not clear since the price varies due to many factors (species, quality, supply…) and it is therefore not easy to separate out the effect of order. A contribution of this paper is precisely to estimate the net (i.e., conditional on everything else) marginal effect of boat order.

The paper is structured as follows. The next section summarizes some previous work on hedonic fish price functions. Next, we describe the fish market and the data. The following section explains the empirical model. After presenting and discussing the results of the econometric estimation of the models, the paper ends with some conclusions.

FISH HEDONIC PRICING STUDIES

Many papers have studied the effect of product characteristics on the market price. In this empirical literature, price is generally modelled as a function of the product characteristics, giving rise to the so-called hedonic price regressions. Hedonic price analysis has its origins in the seminal work of Waugh (1928), who regressed the price per lot of asparagus on three dimensions of quality, namely color, size of stalks and uniformity of spears. The theoretical basis for hedonic pricing was developed much later by Lancaster (1966). In Lancaster's demand theory, consumers obtain utility not from the goods themselves but instead from the intrinsic characteristics of goods.

The analysis of fish prices is a common subject in fisheries economics. In most of the research to date, hedonic functions have been estimated for fish retail prices (Roheim, Gardiner, and Asche 2007). However, few studies have analyzed the factors that explain the price formed at auctions and these have taken quite different approaches. For example, some papers use time-series aggregate data at the auction market level (Sjöberg 2015) while most employ panel data. However, there are few studies that attempt to explain auction prices using bid-level data.

McConnell and Strand (2000) estimated a hedonic price function for tuna using data from the fish auction markets in Hawaii. These are English auctions where each tuna is auctioned separately. They find that species, quality (size, fat content) and total landings are relevant variables in the determination of ex-vessel prices.

Fluvià et al. (2012) analyze the fish auction in the Spanish town of Palamós, on the Mediterranean coast. They estimate hedonic functions for several species, including several fixed effects (buyer, seller, month) and also the time of the day when the transaction took place. An interesting feature of this paper is that, for the case of hake, they estimate a different hedonic function for each of the four size classes of this species.

Lee (2014) estimates a hedonic model of cod prices in the northeast US for the period 2005-2011. He uses auction data at the lot level corresponding to winning bids of the same buyer-seller combination. Controlling for buyer and seller fixed effects, he finds that size, gear, trip length (as an indicator of freshness) and day of the week, among others, influence the ex-vessel price of cod.

Hammarlund (2015) studies the effect of fish characteristics on the price of cod using 731,540 observations corresponding to the sales notes of cod landings by Swedish vessels in Baltic ports between 1977–2011. She estimates hedonic inverse demand functions using a random coefficients model and finds that the total quantity available of each cod size affects the price of different sizes, that is, different sizes are substitutes.

More recently, Gobillon, Wolff, and Guillotreau (2017) study 15 million transactions in the French fish markets over the 2002–2007 period. They are mainly interested in controlling for the unobserved heterogeneity of buyers and sellers. In particular, they pay special attention to specific pairs of buyer-seller matches. They find that unobserved buyer and seller heterogeneity has an important role in the determination of prices.

The role of fish attributes on the ex-vessel price is not the only focus of interest of researchers in fish auctions. Thus, some authors have looked at issues such as the difference between auction prices and direct sale prices (Helstad et al. 2005), the loyalty between buyers and sellers (Gallegati et al. 2011), the spatial integration of auction markets, i.e., whether there are differences in price across regional markets (Gobillon and Wolff 2016), or the declining price anomaly (Salladarré et al. 2017).

In sum the main explanatory variables included in the empirical models of studies estimating hedonic price functions using data from fish auctions are the total amount of fish auctioned in the day, the size of the lot, the main characteristics of the fish (quality and size), the type of gear employed and the season (mainly through monthly dummies). Depending on the structure of data, some control variables, such as day of the week, port of landing, and others, are sometimes included. Finally, unobserved heterogeneity is modelled in some of these papers with the inclusion of buyer and seller fixed effects. In the present study, not only do we include all these variables in our empirical model but we incorporate some additional explanatory variables not previously considered in the literature.

THE AVILES FISH MARKET

The data used in this study were provided by one of the main fish markets in Northern Spain, located in the port of Avilés. The auction takes place Monday through Friday, with two sessions, one in the morning (around 7:00) and one in the afternoon (around 17:00). Once the boats arrive at port, the catch is unloaded in boxes and classified by species and size. If the boats arrive early, the boxes are kept in a large store room and the buyers can inspect the fish in order to get a more accurate idea of certain attributes such as freshness. Before the auction starts, most buyers stop by the warehouse where all catches are kept for visual inspection. Once the auction starts, buyers move to the auction room and they remain there even if some new boats arrive after the auction has begun.

Each box contains a label with the area where the fish were caught, the name of the boat and the freshness grading. The buyers have access to this information in advance of the auction in order to help them prepare their bids. When the auction starts, the boxes are placed on conveyor belts that pass in front of the buyers.[3]

[3] When there are many boxes of the same class for a particular boat, just one is shown on the belt and the rest are kept in the store room.

In Avilés, the auction is done by boat, that is, all the species of one boat are auctioned together. It is important to note that buyers at the Avilés market are not allowed to bid remotely, that is, they must be physically present at the premises where the auction is held.

The bidding system in Avilés is a Dutch auction, also known as a descending-price auction.[4] In this type of auction, the auctioneer sets an initial price above what the product is expected to receive. The clock starts to count down until one buyer stops it. At that moment, the auctioneer asks how many boxes of that lot the buyer is willing to purchase. The buyer can take all of them or just a part, in which case the auction restarts at the current (or a slightly higher) price.

The Avilés auction employs an electronic system to convey the information to the buyers.[5] That is, there are several screens showing the information about the lot being auctioned, including the name of the boat, the weight, the quality and the price. The buyers can stop the auction by pressing a button on their remote-control devices. This system differs from the traditional one, where there is an auctioneer that calls the price out loud and which can still be found in other fish auctions in Spain. It is worth noting that these two systems yield different results. Guillotreau and Jiménez-Toribio (2011) using data from fish auction markets in France present empirical evidence that the introduction of local electronic auction systems produces an increase in both price level and variability.

DATA

The records in our data set refer to individual transactions carried at the fish auction during 2016. We have a wealth of data that includes, among other variables, the price of each transaction, the characteristics of the fish, the gear used to catch it, the type of buyer and the time of the day. There is very precise data on the two main fish attributes, namely size, which is coded from 1 (biggest) to 4 (smallest), and freshness, which is coded using three categories. The price of the winning bids in the

[4] While there are several types of auctions the Revenue Equivalence Theorem states that under certain assumptions, they yield the same result. See Klemperer (1999) or Milgrom (1989) for a review of auction theory.
[5] Electronic auctions have replaced the traditional shout auctions in most fish markets in Europe. Guillotreau and Jiménez-Toribio (2006) review the consequences of the adoption of electronic auctions in French fish markets.

auction refers to a particular lot of fish (for example, 10 boxes of hake), so to make the analysis homogenous we have transformed all records to show the price paid per kilogram.

The data also contain information about buyers and sellers. The different boats were identified by a numerical code, thereby preserving their anonymity. In keeping with this, we have no access to boat characteristics, except for the gear employed. The buyers were also identified through a numerical code but there was information on the type of buyer, which allowed us to classify buyers into three groups: fishmongers, supermarkets, and wholesalers.

Data selection

The number of species auctioned at the Avilés port is very large (over 100) although many of them are not relevant. Table 1 shows the landings of the five main species by weight and by value.

TABLE 1 AROUND HERE

For the empirical analysis we selected hake (*Merluccius merluccius*) since it made up for almost 30% of all the landings and 44% of the value of the fish auctioned at the Avilés fish market in 2016. Hake is also the main species of fish consumed in Spain[6]. Additionally, hake is caught year-round, while other species, such as mackerel or tuna, are seasonal, being mainly concentrated during a couple of months in the year.

The original records were cleaned based on two criteria: unusual values and records that were not interesting for the purpose of our analysis. We deleted some records with zero price. These observations belong to cases where the fish was returned by the client and therefore the sale was annulled. There are also some transactions with very low prices, which correspond to cases involving fish with some type of defect. Since we were not interested in explaining theses unusual cases, those records were deleted. Furthermore, we do not use the records from the morning auction.[7] The reason

[6] According to the Ministry of Agriculture, hake is the most consumed fish species in Spain. In 2019, per capita consumption was 2.6 kg (9,1%) which represented an expenditure of 19.60 € (10%).

[7] The two auctions are independent. In the morning session just big boats that fish in distant waters participate in the auction (also purse seiners, but they do not catch hake). Their fishing trips last for around 10 days. In the afternoon auction the boats are different. They are small or medium-size boats that fish inshore with daily trips. Auctioning in the morning or afternoon auction is not a decision that can be made by the skipper but rather it is

is that the number of boats in this auction is very low, usually between one and four. Since we are interested in studying the role played by the order of the boat in the auction, it does not make much sense to study this issue in a context of very few boats. The final number of records used in the empirical analysis was 15,632.

EMPIRICAL MODEL

The basic model is a hedonic function where the price per kilo is the dependent variable and the explanatory variables are auction characteristics, fish attributes, characteristics of boats and buyers, and a set of control variables. The equation to be estimated is the following:

$$\mathrm{P_{it}} = \alpha + \beta \mathrm{W_{it}} + \gamma \mathrm{X_{it}} + \delta \mathrm{Y_{it}} + \theta \mathrm{Z_{it}} + \mathrm{v_{it}} \qquad (1)$$

where P_{it} refers to the price of transaction *i* in day *t*, W is a vector of auction characteristics, X are fish attributes, Y are buyers and sellers variables, and Z is a set of control variables. Economic theory offers little guidance as to the functional form of hedonic price functions. The most widely used specifications are linear (e.g., Asche and Guillen 2012), log-linear (e.g., Lee 2014) and double-log (e.g., Carroll, Anderson, and Martínez-Garmendia 2001). The double-log specification was selected for this study given the greater flexibility of its marginal effects. Therefore, all continuous variables are in natural logs.

Explanatory variables

The explanatory variables are the following:

a) Characteristics of the auction
    - Fish supply. This variable is the total quantity of hake auctioned in the market on a particular day (SUPPLY_HAKE). It includes the catches of hake in the morning auction, since the behavior of buyers in the afternoon auction depends on their behavior in the morning auction. It is expected that the more fish available on the day, the lower will be

imposed by the auction market. Therefore, boats in the afternoon auction cannot opt to sell their catch in the morning auction and vice versa.

the average price.[8] We also tested the total quantity of fish being auctioned during the day, that is, the landings of all species, but it provided a poorer fit than the supply of hake.

- Previous day's supply. We assume that the quantity auctioned on the previous day can also affect current price, since if buyers could not acquire the desired quantities, they will have an additional incentive to bid. The variable PREVIOUS_HAKE measures the total quantity of hake sold on the previous day.
- Lot size. The auction of each species is carried out by size. That is, given a boat, the auction is carried out first by species, and for each species the different sizes are auctioned separately. When there are large landings of a particular size, the auctioneer decides whether the landings be split into several lots or auctioned together in one big lot. The usual practice is to split homogeneous (species-size) combinations into several (large) lots, since it is expected that the price will decrease with the size of lot. Since the auction market charges a flat rate commission on the fish sales, it benefits from larger prices. For example, Fluvià et al. (2012) include the weight of the lot.
- Number of boats. The variable NBOATS reflects the number of boats that land hake on each day. It is intended to capture whether the behavior of buyers is the same if the entire supply of a species is landed, say, by one vessel or distributed among several vessels. Our hypothesis is that the greater the number of boats (for a given supply), the lower the price. The reason is that a plurality of boats acts as a safety net for buyers in the sense that if one big buyer takes all the fish from the current boat being auctioned, there is still a chance to win a bid if other boats remain to be auctioned.
- Number of buyers. We expect that the higher the number of buyers, the greater the competition will be in the market and therefore the higher the resulting prices. The variable NBUYERS is measured as the number of clients that made at least one purchase

[8] It could be argued that the catch by boats which are auctioned later in the day may not affect the price of the catch by the boat being auctioned at the moment. However, in Avilés buyers have on-screen information not only about the landings that have taken place but also an estimation of the catch of incoming boats.

in the afternoon auction on a particular day. While it would have been desirable to have the number of buyers present in the auction room at the time the lot was being auctioned, this information was not available.

b) Fish attributes[9]

- Size. The main fish attribute is size, which is coded from 1 to 4 (1 representing the largest). We include size dummies labeled D_SIZEX, where X can be VERY LARGE, LARGE, MEDIUM or SMALL. The smallest category is the excluded one.
- Freshness. This is also an important attribute. In Avilés the method used for the quality assessment of fish is the EU scheme, according to the Council Regulation (EC) 2406/96. In this scheme, three grades of freshness are established: E, A and B, where E (Extra) is the highest possible quality. The freshness is decided by visual inspection by the auction market crew when the fish is landed. Since there are three categories, we have included two dummy variables, D_FRESHHIGH and D_FRESHMEDIUM. The excluded category is the least fresh.

c) Buyers and sellers' characteristics

- Gear. In this fishery, hake is mainly caught using three gears: longline, gillnets and trawl. We control for the gear employed by each boat introducing two dummy variables, D_LONGLINE and D_GILLNET. The excluded category are the trawlers.
- Order in the auction. At this fishing market, all the fish caught by each boat is auctioned together (all the species) and the order is determined by the time of arrival at port (first come, first auctioned). The variable BOATORDER takes value 1, 2, … depending on the order the boat was auctioned on each day. This is an ordinal variable (similar to a time trend) and it is included in levels (not in logs). Order (as well as time) increases in units

[9] In this market, the presentation is homogenous since most fish are traded whole, gutted and head on.

and it makes little sense to model it in logs since we are not interested in finding out what happens when order increases by one percent.[10]

- Boat frequency. Undoubtedly, one of the factors that buyers take into account in order to place their bids is uncertainty. Buyers want to minimize uncertainty about the quality of the fish bought, and even though they can inspect the fish previous to the auction, knowing the boat may help them to place their bids. We have constructed a variable measured as the raw frequency count of landings over the year that reflects the “fidelity” of the boat owners to this port (NLANDINGS).

- Type of buyer. It is not common to have information on the buyers. For example, Gobillon, Wolff, and Guillotreau (2017) use buyer fixed effects to account for buyer heterogeneity. Since we have information on the type of buyer winning the bid, we have created three dummy variables: D_FISHMONGER, D_SUPERMARKET and D_WHOLESALER. Salladarré et al. (2017) use the same buyer types. The excluded category is wholesaler.

d) Control variables

- Month: we include monthly dummies (D_MONTH) to control for possible seasonal effects (December is excluded).

- Day of the week: The behavior of buyers is different depending on the day of the week. Salladarré et al. (2017) and Pettersen and Asche (2020) control for the day the week. We have included dummy variables for each of the active days (there is no auction on Saturdays and Sundays). The excluded category is Friday.

- Pre and Post Holidays: The behavior of buyers may be different on the day before and after a holiday. In this paper, ‘holidays’ refer to 12 national and local (regional) holidays

[10] It should be noted that the same numerical value for order (position) appears even when the total number of boats differ. Obviously, it is not the same to auction in tenth place when there are twelve boats than when there are thirty. However, the number of boats in the day is used as an explanatory variable and therefore the estimated marginal effect of boat order is conditional on the number of boats.

that exist in Spain every year. On these holidays, fishmongers and supermarkets are closed. We create two dummy variables, D_HOLIDAYBEFORE and D_HOLIDAYAFTER, which are expected to account for possible differences in the behavior of buyers. We expect these dummies to have a negative sign. The day before a holiday, buyers will slow down their purchases since the fish will not be able to be sold on the following day. The day after a holiday we expect the price to be lower since the boats will fish during the holiday and accumulate the fish of two days for the day after the holiday. This price effect should be partially captured by the dummy of the day after the holiday and partially by the supply variable.

- Special dates. We include dummies for two special periods of the year: Easter week (D_EASTER) and Christmas week (D_CHRISTMAS). Seafood consumption during these holidays spikes in Spain.

In sum, this paper uses not only the traditional variables used in the literature to date (daily and previous supply, size, freshness, gear, time effects…) but also several variables that have not been previously used in fish hedonic functions such as number of boats and buyers, order of the boat, number of landings in the year, and holiday dates.[11]

Descriptive statistics

Table 2 shows descriptive statistics of some of the explanatory variables. Price shows high variability, mainly explained by differences in size and freshness. Lot size also has a large dispersion. This is common since, on a given day, a particular boat might only bring in a very small amount of a particular size, which must be sold separately. The average number of boats landing hake is 17, which is high enough for the purpose of studying the effect of boat order. There is a high number of buyers in this

[11] An important explanatory variable of fish prices is the geographical origin of the fish. This is particularly important in the case of hake. For example, Asche and Guillen (2012) found that origin is the most important attribute in determining hake price at the wholesale level in Spain. This is due not only to different physical characteristics of the fish but to the different degree of Anisakis present depending on the fishing area. Since our boats catch hake on the continental platform with daily trips, there are no differences regarding origin in our sample.

market, especially considering that the buyers must be physically present at the market during the bidding. The dummies for fish size reflect the typical size distribution, with the extreme sizes being the least frequent. Most of the observations (76%) are registered as having high freshness, something expected in a market where most landings for hake come from daily trips.

TABLE 2 AROUND HERE

Table 3 contains information about the boats that land hake in Avilés, grouped by the fishing method employed. Most vessels use longline, followed by gillnets. Longliners rank first in term of catch landed, while the largest landings correspond to the trawlers .

TABLE 3 AROUND HERE

Figure 1 shows the histogram of the number of boats which landed hake on a particular day. On the X axis we have the number of boats that land hake on each day, while on the Y axis we have the number of days in the year that had that number of boats. For example, there were four days with just two boats landing hake. This graph clearly illustrates the validity of our earlier statement that the number of boats is high enough to study the influence of boat order.

FIGURE 1 AROUND HERE

Figure 2 contains the average hake price for each order. The price has a maximum at order 10 and then decreases again. Even though this is an unconditional mean which is affected by all other relevant variables, there seems to be a quadratic relationship between order and price. For this reason, in our empirical model we also introduce a square term for boat order to account for this effect.

While boat order has not been included in previous fish auction studies, two papers have performed a similar analysis when looking at the declining price paradox. Gallegati et al. (2011) rank transactions daily and compute the average price for each rank (i.e., the price of all the first transactions over the sample period, the price of the second transactions, etc.), finding a clear negative relationship between average price and the rank in the auction. They perform this computation for what they call ‘transaction class’, which is a combination of species and size. The same analysis was undertaken by Salladarré et al. (2017) in their study of *Nephrops norvegicus* in France, finding the same pattern. While these two papers find empirical evidence between order in the auction and price, they do so in different framework from ours since they do not control for the effect of other variables that affect price.

FIGURE 2 AROUND HERE

Table 4 describes the activity of buyers, grouped into three categories. Of the 154 different customers who bought hake during 2016, over three-fourths (78.6%) are fishmongers, followed by wholesalers (18.8%), and supermarkets (2.6%). Fishmongers clearly dominate the auction for hake, accounting for 81% of the number of bids won, 61% of all the hake auctioned and 66% of the value of the hake auctioned in 2016. However, their buying pattern is very different from that of larger buyers, since wholesalers and supermarkets purchase higher volumes so that the average value of each bid awarded is significantly higher than that of fishmongers.

TABLE 4 AROUND HERE

ESTIMATION AND RESULTS

Equation (1) was first estimated by pooled Ordinary Least Squares (OLS) using White-robust standard errors. To take advantage of our panel data, we also estimated equation (1) using a Fixed Effects model.[12] The estimations were conducted using Limdep V10.

Estimation by Ordinary Least Squares

[12] While our model contains many explanatory variables, we did not expect correlation to be a problem. This is confirmed by calculation of the Variance Inflation Factor (VIF) for all the explanatory variables. The largest VIF obtained is 6.7, which is well below the threshold level of 10 assumed to signal a warning about the presence of dangerous multicollinearity.

Table 5 contains the results of estimating equation (1) using pooled OLS.[13] In this estimation we are assuming that all observations are independent and therefore we are not accounting for possible sources of unobserved heterogeneity. Variable acronyms starting by 'L_' indicate natural logs, while 'D_' represents dummy variables. We carry out two estimations. In the first one, all observations are included, while in the second, as a robustness check, we take out the days when there were less than five boats, since the order in the auction may not be relevant when there are so few boats.

TABLE 5 AROUND HERE

Both estimations show a good fit. The R^2 (around 51%) is relatively high given that our observations are at the bid level. If we take out the new variables included in this paper, the R^2 drops to 44%, indicating that these variables explain a good portion of the variation of the dependent variable. The 26 estimated coefficients are statistically significant and have the expected signs. Since the estimated coefficients are very similar in the two estimations, we will comment on both of them together.

Starting with the variables which represent auction characteristics, we find that the supply of hake on both the current and the previous day negatively affects the price, as does the size of the lots being auctioned. The presence of more boats lowers the price, which is an interesting result considering that it must be interpreted given the current quantity of fish landed. Thus, the negative sign suggests that buyers have less incentive to bid when a boat is being auctioned in the case where they know that there are more boats remaining than in the case when they know there are no more, or very few more, boats remaining. On the other hand, the number of buyers positively affects the auction price, since more buyers implies greater competition among them. Surprisingly, this variable is not usually included in fish hedonic price functions. One exception is Sogn-Grundvåg, Zhang, and Dreyer (2021), who also find that the number of bidders increases the price in an English auction of Norwegian cod which is conducted online. However, instead of the total number of buyers, they include a set of dummy variables to indicate the number of bidders at each auction, ranging from 1 to 5 or more.

[13] A level-log model was also estimated, yielding similar results. The sign and significance of the estimated coefficients did not change and the R^2 slightly dropped to 49.9.

Fish attributes are also significant and have the expected signs. Thus, the dummies for size are positive and increasing with size, indicating that bigger hake are priced higher. While the positive sign of size is a common result in studies of fish price formation (e.g., Sjöberg 2015), the result depends very much on the type of species being analyzed. In fact, the size that gets the highest price, *ceteris paribus* other characteristics, corresponds to the most-valued commercial size. That is, some big sizes may not be the highest-valued because other sizes are preferred from a commercial point of view. For example, Gobillon, Wolff, and Guillotreau (2017) found that for some species (squid, lobster) the price of the smallest category is higher. They argue that this result can be due to the small sizes being more suitable for most consumers since they are sold in one piece. The dummies for high and medium freshness are positive, indicating that the fresher the fish is, the higher the price.

The numerical interpretation of the coefficients of the dummy variables in our model requires some explanation. Since the dependent variable is in logs, the interpretation of the coefficient of a dummy variable, say γ, is ($e^{\gamma} - 1$) (Suits, 1984). Therefore, in the case of the very large category of hake, its coefficient (0.566) implies that it gets a price premium of 78.9% with respect to the omitted category (small hake). In the same vein, the freshest fish (D_FRESHIGH) is priced 76% higher than the least fresh. Turning now to the gear dummy variables, since the base category is the trawlers, the negative sign for the dummies of both the longliners and gillnetters was not expected, particularly the one for longliners. In fact, it is well known in fisheries that longline fishing usually gets a price premium over the rest of gears. For example, Asche and Guillen (2012) find that hake caught with longline gets a price premium of 1.74 € over trawler hake. Indeed, this is what we find when we look at the unconditional average price in our data set: the average price for longliners is 5.04 €/kg, 4.09 €/kg for gillnetters and 3,33 €/kg for trawlers. The reason for the negative sign of the two passive gears is that they are highly correlated with freshness. In fact, if the dummies for freshness are excluded from the regression, then the coefficient of the dummy for longliners becomes 0.50 and that of gillnetters 0.05. In summary, despite the negative sign in the regression, we conclude that longline is the most valued gear for hake.

The order of the boat in the auction shows a quadratic relationship with the (log of) price since the first term carries a positive sign while its square is negative. This allows us to calculate the optimal order in the auction, which is obtained by taking the partial derivative of the price with respect to the boat order and setting it equal to zero. The result is that the optimum place in the auction is 15 in the first model, and 16 in the second. There are some non-observed factors that can help to explain the quadratic relationship between price and order. One of them is the town where fishmongers come from. The Avilés auction attracts fishmongers from many different towns, including a few fishmongers that come from nearby provinces. It is usually the case that fishmongers that come from towns not close to Avilés arrive early at the auction and try to acquire the fish they need quickly in order to leave as soon as possible for their home towns. Therefore, these fishmongers are willing to pay a premium in order to win bids and finish as soon as possible.

The estimated coefficient of the variable that measures the number of yearly landings (with hake) of each boat is positive. We interpret this result as an indicator that the frequency of landings at the same port provides buyers with precise information on the way skippers manage fish. Quality is not only determined by some easily-observed characteristics, such as size and freshness, but also by other factors that depend on the way the fish is handled inside the boat. Therefore, boats that land in Avilés just once in a while bear a kind of "uncertainty" cost, since buyers are not well aware of their on-boat practices.

With regards to the type of buyers, the dummy for fishmongers is, as expected, positive, indicating that fishmongers stop the auction at higher prices than supermarkets and wholesalers. It should be noted that the classification of buyers into groups is somewhat fuzzy in the sense that some buyers may in fact belong to more than one category. For example, there are fishmongers that also buy and distribute fish for clients that do not wish to spend time daily at the auction, so that these fishmongers act also as wholesalers. This case is important in Avilés because the vast majority of restaurant owners in the region do not attend the auction and have someone on-site to buy for them. It is well known that some of these restaurants look for the best fish (in terms of size and freshness) and since they can get a higher margin than retailers, they are willing to pay a premium for the fish (Gobillon, Wolff, and Guillotreau 2017). This contributes to the large coefficient estimated for the dummy of fishmongers.

With regard to the control variables, the dummies for months are not shown in the table but have been included in the estimation. Most of the coefficients, which reflect the difference with respect to December, are negative and significant, with January being the only month with a positive and significant coefficient.[14] The dummies for days of the week indicate that the day that carries the highest price for hake is Monday, while Friday is associated to the lowest price. This result is due to buyers trying to avoid storage costs over the weekend and because the fish loses freshness and value. Fluvià et al. (2012) also find that hake fetches the highest price on the Monday auction, and a similar result was also obtained by Lee (2014).

The estimated coefficients for the two dummy variables that control for the effect of holidays within the week turn out to be negative. The result can be explained by the fact that buyers have less incentive to buy on the day before a holiday, since their businesses will be closed the day after and there is therefore no need to buy as much. The negative sign for the day after a holiday is probably picking the effect of a larger supply, since in this fishery boats go out every day (except Saturdays and Sundays), even on holidays, and the fish caught during the holidays will be stored and auctioned on the following day together with that day's landings.

Lastly, the dummies for Easter break and Christmas week have positive coefficients. This implies that the consumption of hake increases in those periods, *ceteris paribus* all other relevant variables included in the model. The demand for hake is higher in Easter partly due to a still existing influence of the predominant Catholic religion among the population, which does not allow meat to be eaten during those dates, and also partly due to the increase in population as a consequence of the influx of

[14] The price of hake is highest in January (the unconditional mean is 5.2 €/kg), followed by July (4.88 €/kg), March (4.64 €/kg), and December (4.62 €/kg). The high price in January is explained by the size of hake as well as by the few boats operating in that month, while in July and March the supply of hake is rather low since many boats are fishing tuna (August) or mackerel (March). The negative signs of the dummies for March and July are due to the inclusion of the supply of hake in the model, which takes into account the low supply in those months.

tourists during those holidays. In Christmas week there is also an influx of tourists but hake is a well-established item in many of the typical Christmas dishes.

Estimation by fixed effects

As is well-known, pooled OLS will yield biased and inconsistent estimates of the regression parameters when there is unobserved heterogeneity correlated with the included variables. To avoid this problem, the econometric literature recommends the use of fixed or random effects estimators (Greene 2018). In auction panel datasets there are two types of individuals, boats and buyers. Therefore, following the previous literature we have estimated equation (1) including boat and buyer fixed effects (e.g., Lee 2014).[15] In doing so, we had to exclude all time-invariant variables (since they are perfectly correlated with the fixed effects), which in our case were the gear dummies, the number of landings, and the dummies for buyer type.

The results of estimating equation (2) by OLS including fixed effects are presented in Table 6. We have used all the observations since there are almost no differences when deleting some extreme observations (early and/or late boats). First, we show a baseline case with only boat fixed effects and then the more general case with both boat and buyer fixed effects. There is a slight improvement in statistical fit with respect to the estimations using pooled OLS, with the R^2 increasing to 55.2% and 59.6%.[16] This implies that the main characteristics of boats and buyers were rather well represented in equation (1) with the inclusion of gear, landings and buyer type dummies. The estimated coefficients are similar in sign and magnitude to those in Table 5, and therefore we will not comment on them.

[15] Some authors have opted for specifying fixed effects for observations that match the same pair of buyer and boat. For example, Gobillon, Wolff, and Guillotreau (2017) argue that specific pairing of sellers and buyers can matter for several reasons, such as the difference between remote and onsite buyers (not measured) due to the fact that onsite buyers can observe the fish and even talk to fishers. In the Avilés fish market there is no online sale and there are not significant specific matches.

[16] Gobillon, Wolff, and Guillotreau (2017) find a larger improvement in R^2 (from 48% to 61%) between the pooled OLS regression and the model with buyer and seller fixed effects, although they have fewer control variables than ours.

The optimal boat order in these two fixed effects models is 14 in the case of boat effects and 19 in the case of boat and buyer effects. Again, we confirm the hypothesis that the strategy of trying to be one of the first boats to be auctioned goes against the average price received.

TABLE 6 AROUND HERE

DISCUSSION

Since statistical significance is not the ultimate aim of research, in this section we will try to show the economic significance of the main findings of this paper. We would like to uncover how important some of those variables are for real-life decisions. This is a long-standing debate in econometrics between statistical and economic significance (Goldberger 1981). The best way, perhaps, to look at economic significance is to consider not only marginal effects but also total effects. With this in mind, we have estimated the effect on annual revenues of the three main types of boats that catch hake in this fishery (trawlers, longliners and gillnetters) of arriving at port in different orders.

The revenue from hake for type of boat *i* and order *j* (R_{ij}) is given by the following expression:

$$R_{\mathrm{ij}} = \widehat{\mathrm{P}}_{ij}\overline{\mathrm{Q}}_{\mathrm{i}} \quad (2)$$

where, $\overline{\mathrm{Q}}_{\mathrm{i}}$ is the average annual quota for each type of boat in Asturias in 2020, and $\widehat{\mathrm{P}}_{ij}$ is the predicted average price of hake at each boat order. The latter has been computed adding the marginal effect on price of an increase in order (ΔP_{j}) to the average price received by boats that were auctioned in first place (4,23 €/kg). We have done that for three orders - 10, 20 and 30 - using the following expression:

$$\Delta P_{\mathrm{j}} = \Delta Z(\gamma + 2\delta\bar{Z}) * \bar{P} \quad (3)$$

where, γ and δ are the parameters of Order and Order Squared in equation 1, $\bar{P}$ is the average price of hake, and $\bar{Z}$ is the average order in the interval of the order increase. For example, from order 1 to order 10, ΔZ is 9 and $\bar{Z}$ is 5.5 (which is the midpoint between 1 and 10).

More concretely, we compare the revenues obtained arriving in orders 1, 10, 20, and 30. To approximate the annual revenues from hake, we have calculated the average quota in 2020 for each of the three types of boats.[17] Table 7 shows the estimated revenues.

TABLE 7 AROUND HERE

The difference in annual revenues between boats arriving in 10th place and those that arrive in first place is 4.7%. Boats being auctioned in order 20 get a premium of 6% with respect to those in first place, while the difference for boats in order 30 is 3.7%. It should be noted that these differences are the same in percentage term for the three types of boats.

CONCLUDING REMARKS

We estimate a hedonic price function first by pooled OLS and then including boat and buyer fixed effects. While the results are very similar across all estimated models, the OLS estimation may be biased due to the effect of unobserved heterogeneity. That's why our preferred model is the one with fixed effects. Starting with the variables that represent auction characteristics, we find that the supply of hake on both the current and the previous day negatively affects the price, as does the size of the lots being auctioned. We also get a well-known result: the main characteristics that reflect fish quality, that is, size and freshness, carry a price premium.

The original explanatory variables suggested in this paper also help to explain fish auction prices. The presence of more boats contributes to lowering the price, which is an interesting result considering that it must be interpreted given the current quantity of fish landed. Thus, the negative sign suggests that buyers have less incentive to bid when a boat is being auctioned if they know that there are more boats remaining. On the other hand, the number of buyers positively affects the auction price, since more buyers implies greater competition among them. Surprisingly, this variable is not usually included

[17] We have used the hake quota allocated to boats in Asturias, the region where the port of Avilés is located.

in fish hedonic price functions. The number of yearly landings indicates some sort of loyalty to the port and is rewarded with a price premium; and holidays end up reducing demand and therefore reducing price. Finally, our main variable of interest –the order of the boats in the auction– shows a quadratic relationship with price, which allows us to solve for the optimum place in the auction.

Therefore, we find that it is not a good strategy for skippers to rush to port in order to be auctioned before other boats. In fact, our results show that the average price of hake increases until approximately order (position) 20, and decreases thereafter. This may have important implications for the yearly earnings of boats, with average revenues in position 20 being 6% higher than those in position 1. However, a word of caution is warranted, since trying to use optimal order to maximize revenues obviously cannot be a strategy for all boats. This will only work for the boats that manage to be auctioned around the optimal place, but the total revenue of all the boats taken together is the same. A possible implication of our study for the auction mechanism is that, given that the boat order affects the average price per boat, the auction managers could consider assigning the position in the auction randomly. This can be done daily on the spot with the boats that have arrived before the auction starts, or for a longer period of time, as is done in some Spanish ports on the Mediterranean coast (such as Villajoyosa or Santa Pola) where the fishermen's association establishes a random order at the beginning of the year which rolls daily.

The model shows a good statistical fit given the fact that the data are individual bid transaction data. The motivations of the buyers to bid for the product are very heterogeneous and are affected by some factors which could not be accounted for in the model. One of those factors is the competition from nearby ports. If one observes the behavior of buyers at the auction market, it is noticeable that a good proportion of them is permanently connected to their mobile phones. This is the case of big buyers that buy for supermarkets, or wholesalers that buy for exporters or other big clients. For a large national supermarket chain there is no difference between buying, say, one ton of hake in Avilés than buying it in another port in northern Spain. The hake bought is shipped by truck to a distribution center (often hundreds of miles away) and from there is distributed to the supermarkets of the chain. For this reason, the most relevant supply variable is not the local one but the one of all the competing auction markets.[18] However, these data are not available on a daily basis and therefore the effect of competitors enters the noise term in the model.

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[18] According to the manager of the Avilés fish market, the main competitors are the auction markets in some ports in the nearby region of Galicia (Burela and Cillero) as well as the port of Pasajes in the Basque Country (R. Álvarez, personal communication, April 5th, 2021).

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Table 1. Main species auctioned at the port of Avilés (2016) by weight and by value

	Weight (t)	%	Cum (%)		Value (000€)	%	Cum (%)
Hake	3,700	29%	29%	Hake	14,249	44%	44%
Mackerel	3,642	29%	58%	Albacore Tuna	3,346	10%	55%
Blue whiting	1,667	13%	72%	Mackerel	2,863	9%	63%
Albacore Tuna	773	6%	78%	Blue whiting	2,146	7%	70%
Jack Mackerel	423	3%	81%	Anchovy	875	3%	73%
Total	10,205				23,479		

Table 2. Descriptive statistics

	Mean	St. Dev.	Min	Max
PRICE (€/kg)	4.33	1.91	1	14
SUPPLY HAKE (kg)	15,515	14,576	187	63,030
LOT SIZE (kg)	104.2	217.0	1	12,367
NUMBER OF BOATS	17.7	7.1	3	36
NUMBER OF BUYERS	90.9	13.8	36	115
D_SIZE VERY LARGE	0.11	0.32	0	1
D_SIZE LARGE	0.32	0.46	0	1
D_SIZE MEDIUM	0.33	0.47	0	1
D_SIZE SMALL	0.23	0.41	0	1
D_FRESH HIGH	0.76	0.42	0	1
D_FRESH MEDIUM	0.03	0.17	0	1
D_FRESH LOW	0.20	0.40	0	1
Observations	15,632			

Table 1. Boats and catch of hake by gear

	Number of boats	Number of landings	Catch (kg)	Value (€)	Catch per landing	Value per landing
Longline	60	1543	89,594	425,667	58	276
Gillnet	57	1442	68,905	284,163	48	197
Trawler	18	657	48,279	147,083	73	224

Table 2. Buyers' activity by groups

	Buyers	Fish bought (kg)	Fish bought (€)	Winning bids	Kg/bid	€/bid
Fishmongers	121	125,737	568,577	12,740	10	45
Wholesalers	29	68,895	241,188	2,365	29	102
Supermarkets	4	12,146	47,148	527	23	89
Total	154	206,778	856,913	15,632	13	55

Table 5. Estimation of the hedonic price function by OLS

	All observations		Excluding days with < 5 boats	
	Coefficient	t-Student	Coefficient	t-Student
Constant	1.731***	15.35	1.657***	12.85
L_SUPPLY HAKE	-0.051***	-24.17	-0.050***	-23.51
L_PREVIOUS_HAKE	-0.037***	-18.82	-0.035***	-16.77
L_LOT SIZE	-0.009***	-4.98	-0.008***	-4.70
L_NBOATS	-0.276***	-31.36	-0.302***	-31.05
L_NBUYERS	0.121***	4.27	0.148***	4.70
D_SIZE VERY LARGE	0.566***	55.55	0.567***	55.28
D_SIZE LARGE	0.444***	55.26	0.444***	54.75
D_SIZE MEDIUM	0.146***	19.40	0.142***	18.81
D_FRESH HIGH	0.479***	30.83	0.482***	30.70
D_FRESH MEDIUM	0.079***	3.75	0.078***	3.69
D_LONGLINE	-0.141***	-8.31	-0.143***	-8.36
D_GILLNET	-0.365***	-22.12	-0.365***	-21.94
BOAT ORDER	0.005***	4.51	0.0056***	4.65
BOAT ORDER SQUARED	-0.00018***	-3.83	-0.00017***	-3.61
L_NLANDINGS	0.034***	11.89	0.036***	12.16
D_FISHMONGER	0.110***	14.68	0.110***	14.66
D_SUPERMARKET	0.087***	5.65	0.089***	5.79
D_MONDAY	0.198***	13.35	0.192***	12.02
D_TUESDAY	0.145***	10.41	0.131***	8.76
D_WEDNESDAY	0.056***	4.48	0.052***	3.91
D_THURSDAY	0.115***	8.18	0.112***	7.35
D_HOLIDAY BEFORE	-0.141***	-8.21	-0.161***	-9.15
D_HOLIDAY AFTER	-0.078***	-6.07	-0.076***	-5.86
D_EASTER WEEK	0.234***	11.92	0.240***	12.22
D_CHRISTMAS WEEK	0.078***	3.94	0.064***	3.20
MONTH EFFECTS	YES		YES	
R^2	50.8 %		50.7 %	
Observations	15,632		15,333	

Table 6. Estimation of the hedonic price function including fixed effects

	Boat Fixed Effects		Boat and Buyer Fixed Effects	
	Coefficient	t-Student	Coefficient	t-Student
Constant	1.829	15.57	1.649***	15.53
L_SUPPLY HAKE	-0.050***	-24.31	-0.049***	-24.50
L_PREVIOUS_HAKE	-0.033***	-17.09	-0.033***	-17.71
L_LOT SIZE	-0.009***	-4.31	-0.005**	-2.49
L_NBOATS	-0.274***	-31.27	-0.263***	-31.13
L_NBUYERS	0.130***	4.71	0.140***	5.28
D_SIZE VERY LARGE	0.541***	51.64	0.5246***	51.04
D_SIZE LARGE	0.420***	51.26	0.397***	49.35
D_SIZE MEDIUM	0.137***	18.16	0.139***	18.90
D_FRESH HIGH	0.503***	32.37	0.374***	29.84
D_FRESH MEDIUM	0.141***	6.82	0.075***	4.06
BOAT ORDER	0.005***	3.91	0.007***	5.73
BOAT ORDER SQUARED	-0.0001**	-3.52	-0.0001***	-3.87
D_FISHMONGER	0.105**	14.48	------	------
D_SUPERMARKET	0.077***	5.16	-----	------
D_MONDAY	0.224***	15.25	0.148***	10.36
D_TUESDAY	0.154***	11.26	0.114***	8.69
D_WEDNESDAY	0.090***	7.26	0.048***	4.06
D_THURSDAY	0.129***	9.28	0.078***	5.76
D_HOLIDAY BEFORE	-0.132***	-7.88	-0.145***	-10.63
D_HOLIDAY AFTER	-0.093***	-7.41	-0.088***	-7.25
D_EASTER WEEK	0.209***	10.88	0.188***	10.12
D_CHRISTMAS WEEK	0.090***	4.63	0.076***	4.03
MONTH EFFECTS	YES		YES	
R^2	55.2 %		59.4 %	
Observations	15,632		15,632	

Table 7. Estimated annual revenue of hake quota for different orders in the auction (€)

		Order			
	Hake quota	1	10	20	30
Trawler	45,000	190,350	199,305	201,771	197,343
Longliner	8,500	35,955	37,646	38,112	37,275
Gillnetter	24,000	101,520	106,296	107,611	105,250

Figure 1. Frequency (days) of the number of boats that land hake in a particular day

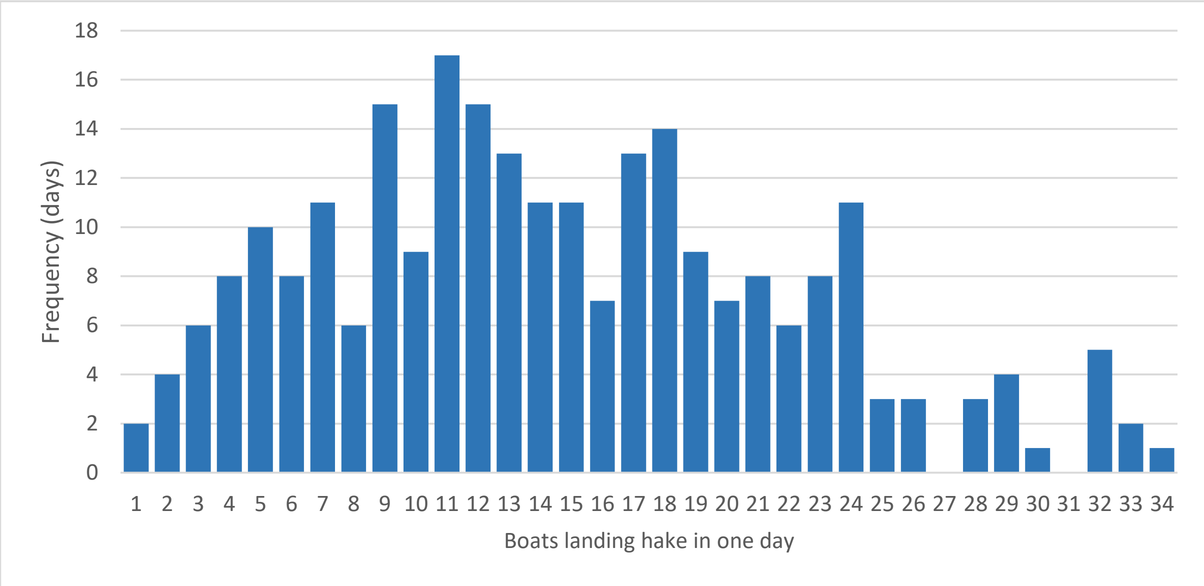

Figure 2. Average hake price (€/kg) as a function of boat order