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Large buyers at a fish auction: The case of the Norwegian pelagic auction

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A B S T R A C T

This paper explores the role of large buyers at the Norwegian pelagic auction. The auction is electronic, with no product inspections and conducted on a first-price, sealed-bid basis. Hedonic price modelling was applied to auction data for mackerel for the main seasons of 2013–2015, which comprise 2447 transactions accounting for a traded volume of 581,613 t. A key finding is that the largest buyers pay lower prices than smaller buyers, all else being equal. For example, holding transaction quantity and fish size constant, the largest buyer pay about 3% less than the small buyers, implying a discount of NOK49.9 million for the three years covered by the study. This is attributed to a better understanding of the auction, including other buyers' valuations. In addition, only the largest buyers can handle the largest catches, so there is less competition and lower prices in this market segment. Another key finding is that, holding other factors constant, the largest buyers pay a lower price for fish size than that paid by small buyers. With transaction quantity held constant, the price discount for fish size is NOK 0.146 (per 10 g) for the largest buyer and the price premium for the small buyers is NOK 0.099 (per 10 g). Findings are discussed and compared with past research focusing on fish auctions. Practical implications are also discussed.

1. Introduction

Auctions are often used to organise fish markets around the world, particularly at the port and wholesale levels of the value chain. Since auctions usually bring many sellers and buyers together and a great variety of fish species is generally available in various sizes, quantities and qualities auctions can reduce transaction costs for sellers and buyers. Auctions are typically organised by sellers, who aim to benefit from competition by extracting the maximum revenue from buyers [19]. Sellers usually decide the auction method and rules [19]. Given the assumptions of the revenue equivalence theorem [16,19,22], the auction type should not matter to sellers because they should always be able to extract the maximum revenue from buyers [19,22].

In the real world, however, fish auctions are not always efficient; this has been shown in several empirical studies that have revealed imperfect competition, for instance different buyers paying different prices for fish of identical quality [4,5,7,9,10]. This is surprising given that information about products is usually readily available at auctions, implying well-informed buyers [10]. However, buyers may differ in many ways, which may lead to differences in their evaluations of product quality and hence their subsequent bidding behaviour. For example, buyers may differ in their experience with, and understanding of, price formation at the auction [13,23]. Over time, some buyers may develop an intimate knowledge of particular sellers and the quality of their products, meaning that they know more about product quality than less experienced buyers [1]. In addition, the quality preferences of buyers' customers may also differ, which may lead to differences in the buyers' evaluations of the quality of a given product at the auction [4,7,9,10]. Buyers also typically differ in the size and capacity of the catches/lots they can process or handle, which may influence their preferences with respect to both the quality and size of catches. For example, in order to avoid idle production capacity and exploit economies of scale, large processing firms might prefer a few large catches of reasonable quality to many small catches of high quality.

In this study hedonic price modelling is applied to examine formation of prices for mackerel at the Norwegian pelagic auction, paying particular attention to the largest buyers at the auction. More specifically, the paper explores whether large buyers pay different prices than small buyers, all other variables being equal. In addition, the paper explores whether large buyers value the size of catches/lots and fish differently from small buyers. Auction data for mackerel over three years (2013–2015), comprising 2447 transactions and accounting for a total of 581,613 t traded for NOK 3.87 billion (€430 million), were analysed. The Norwegian pelagic auction is an electronic auction conducted on a first-price, sealed-bid basis and is the largest auction market for pelagic fish in Europe.

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This study contributes to the literature in several ways. Fish auctions around the world are organised in many different ways for no clear reason [5] and so empirical studies of different types of auction may improve the understanding of the efficiency of different fish auctions [5]. This study is amongst the first to explore price formation at a first-price, sealed-bid auction for fish and seafood (see [14] for a notable exception). The Norwegian pelagic auction also differs from many other fish auctions in that it is electronic, so there is no opportunity for physical inspection of products prior to bidding. This study also focuses on the buyer's perspective, whereas most studies of auctions have focused on the seller's point of view [15]. This is also the first published, empirical study of the Norwegian pelagic auction (see [2] for a conceptual discussion).

The next section provides a detailed description of the Norwegian primary market for pelagic fish, the auction system and the variables included in the study. Section 3 outlines the econometric models used to explore the role of large buyers at the auction. Section 4 presents the results and the key findings and their implications are discussed in Section 5.

2. The pelagic auction and data

2.1. The Norwegian first-hand market for pelagic fish

The primary sale of fish in Norway is legally protected through the Raw Fish Act and is organised by sales organisations that have the exclusive right to co-ordinate the primary sale of fish [2,11]. This includes the right to set minimum prices if sales organisations and buyers' organisations cannot reach agreement on minimum prices. The Raw Fish Act regulating the first-hand market came into force in 1938, following political pressure to protect fishers from the price consequences of buyers' market power. The Norwegian Storsildlaget, which organised herring fishers, was a pioneering organisation formed in the late 1920s to solve the problem of buyers paying a first-hand price that was out of proportion to the price in the export market [11]. The Norwegian pelagic auction was established in the 1970s and is owned and operated by the Norges Sildesalgslag (NSS), the current sales organisation for pelagic fishermen in Norway. The NSS records all transactions in the market and provided the data for this study.

In addition to mackerel, which is the focus of this paper, the auction includes species such as herring, horse mackerel, sprat, blue whiting, capelin and sand eel. Mackerel is the most important species at the auction in terms of traded volume and turnover. The main mackerel season is short, usually lasting three to four weeks in September and October. The data cover the main seasons in 2013–2015 and comprise 2477 transactions. The mackerel were mainly caught by large purse seine vessels (76) and medium-sized coastal purse seiners (around 150). Trawlers and small coastal vessels fishing with hand lines also caught a small share. This study only includes purse seiners, whose share of the Norwegian quota was a little more than 75% in each of the sample years.

2.2. The auction system

The auction is conducted online on the NSS auction site (www.sildelaget.no), so physical inspection of the fish at the time of bidding is not possible. There are four daily auctions throughout the year. Each auction lasts for one hour, with the first auction of the day starting at 7 a.m. and the last auction ending at 10:30 p.m. Note that due to the highly perishable nature of mackerel and the fact that it is sold as fresh fish, it is very important for sellers to clear the market [20]. It also implies that buyers have a strong incentive to get fresh fish on a daily basis to avoid having idle production capacity.

Immediately after a vessel has finished its catch operation the skipper sends a catch report to the NSS. The catch report is based on samples of at least 20 kg of fish per 100 t taken while pumping the fish on board and forms the basis for the auction and bidding. Of particular relevance to prospective buyers is the information about the size of the catch and the average size of fish for the whole catch. The latter is an important attribute in downstream markets, with larger mackerel commanding higher prices in key export markets, such as Japan. For example, in 2013, mackerel in the 'above 600 g' category sold for an average export price (fob) of NOK 30 (€3.33) per kilogramme, whereas the equivalent price for the smallest size group of 200–400 g was only NOK 8.5 (€0.94) [12]. However, it should be noted that the largest size category only accounted for 1% of exports in 2013, whilst the smallest category accounted for 30%. Nevertheless, the strong preference for large mackerel should be reflected in the prices achieved at the auction. During the last 15 years, the average size of mackerel has decreased from approximately 550 g to 410 g in 2015. As fish size has reduced, the price premium for larger mackerel has increased [12]. The catch report also includes information on the content of the stomach, which influences the rate of deterioration of fish quality [6,24].

The captain of the vessel also states primary and secondary bid areas, within the northern and southern ports on the Norwegian coastline, where he would like his catch to be auctioned. Selecting a bid area with many potential buyers increases the chances of higher competition and prices, but it may also result in a longer shipping time (the range is between 3 and 72 h) and hence increased variable costs for the vessel, because the bid price includes delivery to the quayside of the buyer's facility. A longer shipping time also implies reduced quality, particularly in the form of fillet gaping [3].

Buyers have the option to set quantity limits for their bids, that is, they can state a maximum quantity (in total or by species) that they will buy at a given auction. This option is available not only to encourage more bids but also to prevent buyers winning more catches than they can freeze (which is necessary because of the high perishability of mackerel) within a short timeframe. If a buyer wins more catches than the quantity limit it has specified, the NSS will allocate the surplus catches to the next-in-line bid. Buyers also have the option to state the maximum number of vessels (catches) they want to receive. This is because buyers have limited quay capacity (usually only one vessel can deliver its catch at a time) and the fish must be frozen as soon as possible in order to preserve quality. In addition, it is generally more cost-effective to receive one large catch than two smaller ones.

In a first-price, sealed-bid auction buyers are only allowed to place one bid per lot and do not know what other bids have been made. The highest bid wins. As soon as an auction has finished, all information, including the size of bids and the corresponding bidder, are made available online to all participants. The NSS does this to ensure that the auction system is transparent and trustworthy. The information can be used by both buyers and sellers to learn how supply affects prices as well as how different buyers perform at the auction. The NSS sets a minimum, or reserve, price at the beginning of each season.

Twenty-six buyers participated in the auctions during the three-year time-period were analysed. The largest buyer had 10 processing facilities with a total freezing capacity of 5000 t of mackerel per day. Processing plants conduct primary processing which consists of sorting the mackerel by size and then packing and freezing them whole in 20 kg boxes for export markets. In 2015 61,600 t were exported to Japan and 49,000 t to China, where the majority of the fish was further processed and re-exported to Japan [17]. Thus in 2015 approximately 31% of Norwegian mackerel exports were sold, directly or indirectly, to the Japanese market. Other important markets were South-Korea, Nigeria, Turkey and Egypt.

Table 1 displays summary statistics for purchased quantities, prices and average fish sizes, for the top 20 buyers over the three-year observation period. Table 1 shows that on average buyer 1 paid a lower price than many of the other buyers, but also bought smaller fish on average. Table 1 also shows that average prices varied substantially over the three-year observation period. The low prices in 2014 can be explained by several factors, including strong competition in the

Table 1
Summary statistics for the top 20 buyers.

	Price (NOK)		Quantity (tonnes)		Fish size (100 grammes)	
Buyer ID	Mean	Std. dev.	Total	Std. dev.	Mean	Std. dev.
All buyers	8.30	1.39	581,613	169	3.74	3.14
Buyer 1	8.10	1.31	220,785	176	3.73	3.16
Buyer 2	8.43	1.38	78,176	158	3.78	2.87
Buyer 3	8.22	1.13	49,162	168	3.75	2.60
Buyer 4	8.61	1.23	34,057	138	3.80	2.28
Buyer 5	8.03	1.27	30,910	214	3.80	2.08
Buyer 6	8.05	1.79	29,888	188	3.59	5.83
Buyer 7	8.38	1.31	26,730	171	3.80	2.04
Buyer 8	9.06	1.59	24,458	171	3.75	3.36
Buyer 9	8.52	1.33	16,025	124	3.85	2.33
Buyer 10	8.22	1.17	13,847	83	3.73	2.73
Buyer 11	8.77	0.97	11,220	151	3.78	1.81
Buyer 12	8.26	1.32	10,733	93	3.68	2.62
Buyer 13	7.87	1.20	9890	113	3.71	2.04
Buyer 14	9.05	0.70	7310	82	3.86	1.69
Buyer 15	7.57	0.66	5550	225	3.68	2.04
Buyer 16	7.76	1.48	3310	113	3.58	2.73
Buyer 17	7.16	0.95	3235	175	3.79	1.69
Buyer 18	9.07	0.56	1915	132	3.71	1.19
Buyer 19	8.72	0.62	1875	121	3.64	2.10
Buyer 20	8.23	1.40	1490	48	3.79	2.22
5th quintile	8.32	1.38	222,193	173	3.75	3.36
4th quintile	8.59	1.36	92,280	150	3.78	2.62
3rd quintile	8.17	1.25	36,793	128	3.71	2.40
2nd quintile	8.06	1.32	9400	153	3.75	1.90
1st quintile	11.82	0.95	163	18	3.51	0.62
2013	9.07	1.20	135,358	142	3.55	3.56
2014	7.29	1.22	242,394	174	3.76	2.55
2015	8.89	0.86	203,862	173	3.91	2.33

Japanese market, where Norwegian mackerel compete against local mackerel. Some of the differences may also stem from differences in the stored (frozen) stocks held by buyers in these years, which would have affected their demand. If they have mackerel in storage from the previous season, Japanese importers may scale back their purchases, which in turn may affect the bidding behaviour of Norwegian buyers at the auction.

Table 1 also indicates substantial buyer concentration. The 5 and 10 largest buyers accounted for 71% and 90% of the traded volume, respectively. In contrast, the top 10 vessels only accounted for 14.6% of the traded volume, and no individual vessel accounted for more than 2%. It can also be seen that average fish size varied across buyers, indicating differences in preferred fish size. Due to its very dominant market share, buyer 1 was treated as a category in the econometric analysis. The remaining 25 buyers were grouped into five quintiles on the basis of total purchase quantity during the three years covered by the data. Thus the 5th quintile comprises buyers 2–6; the 4th quintile buyers 7–11 and so on. Table 1 shows that, together, the five buyers in the 5th quintile purchased more than 222 thousand tonnes, a little more than Buyer 1. Together buyer 1 and the buyers in the 5th quintile purchased about 76% of the total traded volume, illustrating the high concentration on the buyer side of the market. Table 1 also shows that price paid and the average size of purchased fish varied between the quintiles.

Fig. 1 shows traded volumes and average prices for the three seasons over the 2013–2015 observation period. Inspection shows that the 2014 and 2015 seasons were different from the 2013 season in that the traded volume for September was much lower in 2013 than in 2014 or 2015. Average price was lower in 2014 than in the other two years.

2.3. Variables included in study

Table 2 shows descriptive statistics for the variables included in the analysis. Inspection shows that the mean price of mackerel was NOK 8.30 and that the average fish size was 374 g with a relatively low standard deviation. The standard deviations for transaction quantity and daily quantity are substantial, indicating large daily variation in the quantity of mackerel traded at the auction, mainly due to small quantities being traded at the end of the season (Fig. 1). Table 2 also shows three groups of dummy variables, i.e. top buyers, feed and bid area. Under the dummy-coding technique the reported mean is the observations (deals) within each category as a proportion of the total. For example, buyer 1 accounted for 36% of deals during the sample period and the 5th quintile accounted for 37%.

Moreover, Table 2 shows that Feed 2 (nearly empty stomach) and Feed 3 (partially full stomach) are the most frequent Feed categories, at 37% and 59% of deals, respectively. Only 1% of deals involved fish classed as Feed 1, representing an empty stomach and hence the best quality. Bid areas 1–5 accounted for 58% of deals and 69% of volume traded. Note that large buyers, including buyer 1 had processing plants in all five bid areas.

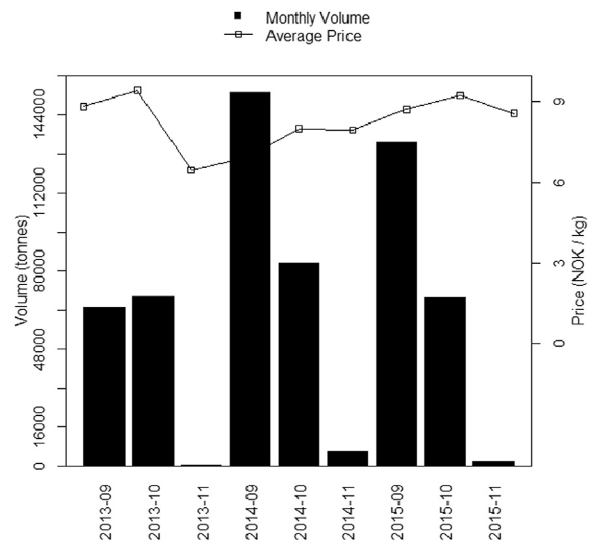

Fig. 1. Transaction volume and the average price of mackerel at the auction, by month.

Table 2
Descriptive statistics for variables.

Variable	Description	Mean	Std. dev.
Price	NOK/kg	8.30	1.39
Size	100 grammes	3.74	0.314
Transaction quantity (TQ)	Transaction quantity (tonnes) of deals	238	169
Daily quantity (DQ)	Daily aggregate quantity (tonnes) for all deals	6984	3940
Top Buyers			
Buyer 1	1, if buyer 1, otherwise 0	0.36	
5th quintile	1, if buyer 2–7, otherwise 0	0.37	
4th quintile	1, if buyer 8–11, otherwise 0	0.16	
Feed			
Feed 1	1, if feed = 1, otherwise 0	0.01	
Feed 2	1, if feed = 2, otherwise 0	0.37	
Feed 3	1, if feed = 3, otherwise 0	0.59	
Bid area			
Bid area 1	1 for bid area 1, otherwise 0	0.23	
Bid area 2	1 for bid area 2, otherwise 0	0.14	
Bid area 3	1 for bid area 3, otherwise 0	0.08	
Bid area 4	1 for bid area 4, otherwise 0	0.08	
Bid area 5	1 for bid area 5, otherwise 0	0.05	

Note: Feed 1 = empty stomach, Feed 2 = nearly empty stomach, Feed 3 = partially full stomach.

3. Model and econometric analysis

Previous econometric studies of fish auctions have shown that factors such as transaction quantity, daily sales quantity and seasonality are important determinants of fish prices [4,7,8,13]. In this study the following potential determinants of auction price were analysed: transaction quantity, daily sales quantity, average fish size, stomach contents (feed), bid area and seasonality (weeks).

In the introduction it was argued that buyers may serve customers/markets with varying preferences with respect to fish size and quality. Buyers of different sizes are also likely to differ in their capacity to handle large volumes, which may influence their preferences with respect to quality and quantity (size of catch) and hence their bidding behaviour at the auction. As described in the previous section, an individual dummy was set for the largest buyer ($buyer_1$) and the other buyers were categorized into five quintiles on the basis of purchase quantity. The 5th and 4th quintiles were added to the model as two additional dummies to allow a more detailed exploration of the role and behaviour of large buyers. Interactions between daily sales quantity, transaction quantity and fish size and the largest buyer, the 5th quintile, and 4th quintile were included in the model to enable exploration of potential price differences between large buyers and small buyers. This yielded the following model specification:

$$\begin{aligned}\log(p_i) = {} & a_0 + b_1\log(Daily\_Quantity_i) + b_2\log(Transaction\_Quantity_i) \\ & + b_3\log(Fish\_Size_i) + \sum_{k=1}^{3} c_k Feed_k + \sum_{m=1}^{5} d_m Bid\_Area_m \\ & + \sum_{n=1}^{3} e_n Buyer_n + \sum_{n=1}^{3} f_n\log(Daily\_Quantity_i){:}\ Buyer_n \\ & + \sum_{n=1}^{3} g_n\log(Transaction\_Quantity_i){:}\ Buyer_n \\ & + \sum_{n=1}^{3} h_n\log(Fish\_Size_i){:}\ Buyer_n + \sum_{o=2}^{32} w_o Week_o \\ & + Residual_i \end{aligned} \tag{1}$$

where i represents the number of transactions during the sample period; log is the logarithm function; *Daily-Quantity* is the daily quantity sold at the auction; *Transaction-Quantity* is the quantity of each transaction; *Fish-Size* is the average size of the mackerel in each transaction. *Feed* is represented as dummy variables, with Feed 1 (empty stomach) regarded as the best quality, Feed 2 is the second best quality, and so on (Feed 4 and Feed 0 (no information provided by sellers) were set as base). *Bid-Area* is represented by dummy variables for each of the five largest bid areas. *Week* is represented as dummy variables covering all weeks included in the data except for the base: the first week. The error term, *Residual,* captures other unobserved factors that affect price.

The coefficients of the dummy variables *Feed*, *Bid-Area* and *Week* are interpreted as price differences (as percentages) between the variables and the base, holding other variables constant. For example, the price of mackerel with $Feed = 1$ is 100* c_1% more expensive than mackerel with $Feed = 4$ (and 0). The coefficients of the numeric variables are interpreted as elasticity. Take *Fish-size* as an example, ignoring all the numeric variables except for *Fish-size* and setting all dummy variables to zero allows Eq. (1) to be reduced as follows:

$$\log(p_i) = a_0 + b_3\log(Fish\_Size_i). \tag{2}$$

The coefficient b_3 represents the elasticity of price with respect to *Fish-Size* for the small buyers (the base). For example, a 1% change in fish size results in a b_3% change in price. The largest buyers may have different price elasticities from smaller buyers, as reflected in the estimation of interaction terms. Further, setting the dummy $Buyer_1 = 1$ yields:

$$\begin{aligned}\log(p_i) = {} & a_0 + b_3\log(Fish\_Size_i) + e_1 Buyer_1 \\ & + h_1\log(Fish\_Size_i){:}\ Buyer_1 = a_0 + e_1 \\ & + (b_3 + h_1)\log(Fish\_Size_i) \end{aligned} \tag{3}$$

Thus, h_1 in Eq. (3) is the particular rotation impact of the largest buyer on the auction price [25,27]. The combination of $(b_3 + h_1)$ is the change in price in response to a one percent change in fish size, for the largest buyer. However, this impact is affected by the particular shift impact e_1. The total impact of a one percent change in fish size on price can be calculated as the mean price ($\hat{p}$) for the largest buyer, using the formula: $p^* = e_1 + (1 + b_3\% + h_1\%)\hat{p}$. The total impact expressed in NOK is therefore $p^* - \hat{p}$.

In the case in which all estimated coefficients are significant, the fitted prices for the base transactions (with all dummy variables equal to zero) and the largest buyers (with $Buyer_1 = 1$) can be calculated. That is:

$$\begin{aligned}\log(\hat{p}_{small\ buyers}) = {} & a_0 + b_1\log(Daily\_\hat{Q}uantity) \\ & + b_2\log(Transaction\hat{\_}Quantity) + b_3\log(Fish\hat{\_}Size) \end{aligned} \tag{4}$$

$$\begin{aligned}\log(\hat{p}_{buyer\ 1}) = {} & a_0 + e_1 + (b_1 + f_1)\log(Daily\_\hat{Q}uantity) + (b_2 \\ & + g_1)\log(Transaction\hat{\_}Quantity) + (b_3 + h_1)\log(Fish\hat{\_}Size) \end{aligned} \tag{5}$$

where $\hat{p}$ is the fitted price, and other variables with ^ are the mean values. Replacing the dummy for the largest buyer with the dummy for the 5th quintile yields the fitted price for the corresponding buyer group, and similarly for the 4th quintile. Comparison of these fitted values can reveal differences between prices paid by the large and small buyers.

In order to determine whether large buyers paid different prices from small buyers, restrictions were set on the base model (Eq. (1), Model A). That is, a more restrictive model was tested against Model A (with no restrictions) and other less restrictive models. The restrictive models and their restrictions are listed below[1]:

Model	Restriction	Null hypothesis
A	No restriction	The base model, Eq. (1)
B	$e_n = f_n = g_n = h_n = 0$, for n = 1,2,3	Buyer size has no impact on price
C1	$e_n = 0$, for n = 1,2,3	Buyer size has no shift effects on price
C2	$f_n = g_n = h_n = 0$, for n = 1,2,3	Buyer size does not influence price through interactions with daily quantity, transaction quantity or fish size
D1	$f_n = 0$, for n = 1,2,3	Buyer size does not influence price through interactions with daily transaction quantity
D2	$g_n = 0$, for n = 1,2,3	Buyer size does not influence price through interactions with transaction quantity
D3	$h_n = 0$, for n = 1,2,3	Buyer size does not influence price through interactions with fish size

The B models and model C1 are nested in the previous less restrictive model, i.e. Model B against Model A and Model C1 against Model B. The nested model can be tested sequentially until rejection occurs [26]. As Models C1 and C2 and Models D1, D2, and D3 are not uniquely ordered restrictions all possible orderings were tested against the less restrictive models. For example, if restrictions associated with Model C1 were to be rejected, Model C2 would be tested against Model B (or A, depending on the test results of the nested models). The testing of Models D1, D2, and D3 against the less restrictive models could take

[1] As suggested by a reviewer, C and D models have restrictions on both shift effect and interaction terms for each numeric variable. Models with these restrictions were rejected so the D models were tested directly against a less restrictive model.

Table 3
The test results of models specified.

Model	Against model	Restriction	DF	p-value
B	A	$e_n = f_n = g_n = h_n = 0$, for n = 1,2,3	12	< 0.01
C1	A	$e_n = 0$, for n = 1,2,3	3	< 0.01
C2	A	$f_n = g_n = h_n = 0$, for n = 1,2,3	9	< 0.01
D1	A	$f_n = 0$, for n = 1,2,3	3	0.11
D2	D1	$g_n = 0$, for n = 1,2,3	3	< 0.01
D3	D1	$h_n = 0$, for n = 1,2,3	3	< 0.01

Note: DF, abbreviation for degrees of freedom. The p-value is based on the F-test.

place in various sequences.

4. Results

The first step of the modelling process was to test the restrictive forms of Model A, that is, restrictions associated with Models B-D3. Following the test procedure outlined above, these restrictions were tested using an F-test. Models B and C1 were firmly rejected at the 0.01 level of significance, as shown in Table 3. According to the test procedure, Model C2 was then tested against Model A, rather than Models B or C1. The p-value indicates rejection of the restrictions associated with model C2 as well, so the restrictions for the interaction terms (Models D1-D2) were tested against Model A. Models A and D1 were statistically equivalent at a p-value = 0.11, implying that the restriction for Model D1 (interaction terms between the daily transaction quantity and buyer dummies) cannot be rejected. Subsequently, Models D2 and D3 were tested against Model D1, with both results indicating rejection of the restrictions in Models D2 and D3. Hence one can conclude that Model D1 fitted the data better than the other models.[2]

The parameter estimates and goodness-of-fit for Model D1 are reported in Table 4. For comparison the estimation results for Model A are also reported in Table 4.[3] The robust standard error of both models was estimated for inference of the estimated coefficients. The high adjusted R-squared values (0.8088 for Model A and 0.8085 for Model D1) indicate that a high share of the variation in prices is accounted for by the variables included in the models. In Model A the interaction terms between *Daily-Quantity* and buyer dummies were not significant, which is in line with the test results reported above.

This section discusses the estimates reported for Model D1 in Table 4. Table 4 shows that the Model D1 estimate for daily quantity (*Daily-Quantity*) was − 0.034, implying that a 10% increase in daily quantity at the auction resulted in a 0.34% decrease in price. The negative effect of daily quantity on prices was small, but expected and can probably be explained by the reduction in competition as buyers' production capacity is taken up. The results for Model D1 also show that the estimate for *Transaction-Quantity* was significant and negative (− 0.089), implying that a 10% increase in transaction quantity led to a 0.89% decrease in price. Lower transaction costs are normally associated with larger (and hence fewer) transactions, so the negative relationship between price and transaction quantity is not surprising. In addition, the largest catches exceed the processing capacity of smaller buyers, in effect reducing the number of potential bidders. The estimate for *Fish-Size* was 0.426, implying that a 10% increase in average fish size leads to a 4.26% increase in price, indicating a strong buyer preference for large mackerel.

The estimates for Feed 1 (empty stomach), Feed 2 (nearly empty stomach) and Feed 3 (partially full stomach) were significant but negative. Discussions with the auction house and with several buyers and skippers revealed that skippers are typically reluctant to report an uempty stomach (Feed 1) because they are afraid that the buyer will complain if they come across food content during their inspections of fish at the plant. There is not much difference between 'no food' (Feed 1) and 'a little food' (Feed 2), so skippers admitted to misreporting Feed 1 as Feed 2 or 3 as a rightful complaint by the buyer would result in a price reduction. Moreover, because full stomachs (Feed 4) are associated with lower prices, skippers admitted to misreporting this as Feed 2 or Feed 3. Thus misreporting probably contributes to the counter-intuitive estimates. Table 4 also shows that, with other factors constant, buyers in two of the five largest bid areas (in terms of traded quantity) pay a higher price compared to buyers in the other bid areas, indicating higher competition in these areas than the base areas.

In Model D1 the estimates for the largest buyer, the 5th quintile and the 4th quintile were significant and negative. This implies that if other factors are constant, large buyers pay a lower price than small buyers and this was confirmed by the computed interval estimation, using robust standard error. It can also be seen that, holding other factors constant, the price differential between buyer 1 and the smallest buyers is greater than the price differential between buyers in the 5th quintile and the smallest buyers. This indicates a monotonic pattern and provides strong evidence that auction prices are influenced by buyer size. Next, buyer behaviour is explored using the estimated coefficients of the interaction terms.

Table 4 shows that all coefficients of these interaction terms in Model D1 were positive and significant. Because the coefficient for *Transaction-Quantity* was negative (− 0.088), the positive estimates for the interactions between buyer size and transaction quantity imply that

Table 4
Parameter estimates.

	Model A		Model D1	
Variable	Estimate	RobustSE	Estimate	RobustSE
Intercept	2.323[a]	0.152	2.325[a]	0.154
log (Daily quantity)	− 0.030[a]	0.008	− 0.034[a]	0.003
log (Transaction quantity)	− 0.089[a]	0.009	− 0.0886[a]	0.008
log (Fish-Size)	0.407[a]	0.132	0.426[a]	0.120
Feed (base: 0/4)				
Feed 1	− 0.179[a]	0.042	− 0.181[a]	0.042
Feed 2	− 0.088[a]	0.029	− 0.088[a]	0.029
Feed 3	− 0.089[a]	0.029	− 0.089[a]	0.028
Bid area (base: other)				
Bid area 1	0.020[a]	0.006	0.020[a]	0.006
Bid area 2	0.0003	0.005	− 0.0001	0.005
Bid area 3	0.007	0.006	0.007	0.006
Bid area 4	0.017[a]	0.005	0.016[a]	0.005
Bid area 5	0.009	0.008	0.009	0.008
Buyer (base: small buyers)				
Buyer 1 (the largest)	− 1.488[a]	0.155	− 1.510[a]	0.158
5th quintile	− 1.477[a]	0.152	− 1.474[a]	0.154
4th quintile	− 0.680[a]	0.248	− 0.685[a]	0.261
Buyer : Daily quantity (DQ)				
log(DQ): Buyer 1	− 0.010	0.009		
log(DQ):5th quintile	0.0001	0.009		
log(DQ):4th quintile	− 0.004	0.010		
Buyer : Transaction quantity (TQ)				
log(TQ): Buyer 1	0.099[a]	0.009	0.0984[a]	0.009
log(TQ):5th quintile	0.105[a]	0.009	0.105[a]	0.009
log(TQ):4th quintile	0.037[b]	0.016	0.035[b]	0.014
Buyer : Fish-Size				
log(Fish-Size): Buyer 1	0.786[a]	0.135	0.743[a]	0.120
log(Fish-Size):5th quintile	0.703[a]	0.135	0.702[a]	0.120
log(Fish-Size):4th quintile	0.401[b]	0.187	0.383[b]	0.173
Adj. R-squared	0.8088		0.8085	

[a] Significance levels: $p \le 0.01$.
[b] Significance levels: $p \le 0.05$.

[2] Changing order in which Models D1-D3 are tested does not influence the results, implying that Model D1 represents the best fit with the data.

[3] The seasonality dummies are omitted from Table 4 to save space. Most of the seasonality dummies were positive and significant, with the exception of weekly dummies for September 2014, which were negative and significant and consistent with the lower prices in that period.

large buyers were less sensitive to changes in transaction quantity than small buyers. The coefficients for interaction terms between buyers and fish size were significant and positive. Combining the estimate for fish-size and these interaction terms indicates that the price elasticity with respect to fish size is 1.169 (= 0.426 + 0.743) for the largest buyer, 1.128 (= 0.426 + 0.702) for the buyers in the 5th quintile, and 0.809 (= 0.426 + 0.383) for the buyers in the 4th quintile.

Price changes (relative to the mean price) following a 10% increase in *Transaction-Quantity* (or *Fish-Size*) were calculated for large and small buyers, taking account of both shift and rotation effects. This shows that with a 10% increase in transaction quantity, prices decreased by NOK 1.502, NOK 1.460, and NOK 0.730 per kilogramme for the largest buyer, the 5th quintile, and the 4th quintile, respectively.[4] For small buyers, the corresponding price reduction is only NOK 0.0752. This is a strong indication of a monotonic relationship between buyer size and transaction size and is probably due to the fact that the largest buyers have the largest processing capacity and are the only ones that can handle very large catches.

Moreover, a 10% increase in fish size resulted in price decreases of NOK 0.545 and NOK 0.527 per 100 g for the largest buyer and the 5th quintile respectively, and an increase of NOK 0.00306 per 100 g for the 4th quintile, respectively, whilst the price increase was NOK 0.361 per kilogramme for small buyers. This is a clear indication that buyer size is also associated with valuations of fish size. By taking the average fish size for these buyers into account, the calculated price premium/discount is NOK –1.46, NOK −1.41, NOK 0.0081, and NOK 0.99 per 100 g for the largest buyer, the 5th quintile, the 4th quintile, and the small buyers, respectively.

Replacing the parameters in Eqs. (4) and (5) with the significant estimations and the values of the numeric variables yields the fitted prices (in logarithmic form) for the larger and small buyers.[5] The means of the fitted value were 2.112, 2.128, 2.141, and 2.139, which correspond to NOK 8.265, 8.398, 8.508, and 8.491 for the biggest buyer, the 5th quintile, the 4th quintile, and the small buyers, respectively, indicating that in absolute terms the largest buyer and the 5th quintile buyer group paid less than small buyers. To determine whether these price differences were significant a bootstrap analysis was conducted. The one-way *t*-test results and bootstrap statistics are reported in Table 5.

Overall the test results presented in Table 5 indicate a monotonic relationship between price and buyer size, for all given values of transaction size and fish size. The exception is the test result for the mean difference between prices paid by the 4th quintile buyers and the small buyers. Transforming the logarithmic prices to prices in NOK shows that the largest buyer paid NOK 0.226 per kilogramme less than the small buyers, and that the buyers in the 5th quintile paid NOK 0.093 less than the small buyers. Taking the total purchase quantity in the sample period into account (see, Table 1), it was estimated that the largest buyer paid NOK 49.9 million less than they would have paid if they purchased the same quantity at the prices paid by small buyers. The five buyers in the 5th quintile would have gained a combined rebate of NOK 20.7 million on the quantity they purchased had they paid the same price as small buyer. The lower prices paid by the large buyers mean they have lower raw material costs, which has a direct, positive influence on their profitability, whilst the income of the sellers that trade with them is negatively affected.

Table 5
T-tests for differences between fitted prices for the large and small buyers.

Mean of fitted price for (log $\hat{p}_1$)	Against: mean of fitted price for (log $\hat{p}_2$)	Bootstrap statistics	p-value (H_N: log $\hat{p}_1$ > log$\hat{p}_2$)
The largest buyer	5th quintile	− 5.62	< 0.01
The largest buyer	4th quintile	− 11.3	< 0.01
The largest buyer	Small buyers	− 9.91	< 0.01
5th quintile	4th quintile	− 5.00	< 0.01
5th quintile	Small buyers	− 4.06	< 0.01
4th quintile	Small buyers	0.63	0.76

Note: Bootstrap statistics are based on 999 replicates.

5. Discussion

A key finding of the study is the strong evidence that prices at the Norwegian pelagic auction are influenced by buyer size, that is, large buyers pay lower prices than small buyers, all other things being equal. Another key finding is that large buyers benefit from a greater quantity discount than small buyers. The results also reveal that buyer size is associated with valuation of fish size, probably reflecting differences in the fish size preferences of the target customers/markets of buyers of different sizes. Holding other factors constant, the price premium paid by the largest buyers for fish size is lower than that paid by small buyers.

These findings indicate a market that is not perfectly competitive, thus corroborating a range of other empirical studies revealing price dispersion in auction markets for fish and seafood e.g., [4,7–10,13]. Below, the price differences revealed are explored in more detail to shed light on the more general question of why there is imperfect competition in fish auction markets, which should, in principle, be highly competitive [9,21].

The finding that the largest buyers pay lower prices than smaller buyers is surprising, as one might expect that large buyer would need to pay higher prices to maintain their high market share [14]. This finding also contradicts Kleijnen and van Schaik [14], who found that large buyers in the sealed-bid auction for Netherland mussels in Yerseke town paid higher prices than smaller buyers. One possible explanation for this difference is that all bidders in the mussel auction market are large enough to bid for all lots, which is not the case in the Norwegian pelagic auction, where only the largest buyers can handle the largest catches/lots, meaning less competition and lower prices for these lots. The calculated price changes in response to both the shift and rotation effects, demonstrate that the largest buyers achieve the largest price reductions when transaction quantity increases. Thus the different market contexts in the two studies may at least partly explain the differences in findings.

The lower prices may also be due to the fact that some of the largest buyers, unlike the smaller buyers, employ specialist buyers who presumably have a better understanding of the auction system and an ability to exploit changes in supply and demand. Over time these expert buyers probably develop a detailed knowledge of the other processors' production capacities, cost structures, valuations, customers and bidding behaviours and they are also likely to have intimate knowledge of the quality of fish delivered by particular vessels and skippers. As noted above, the auction house releases all information about all bids and bidders immediately after an auction has finished. Because fresh mackerel is highly perishable and must be frozen as soon as possible to "lock-in" its quality, information about the winning bids of competitors is probably very useful for buyers who know the production capacity of their competitors as it would make it possible to anticipate other buyers' need for additional catches and hence their likely valuations at subsequent auctions. In this way skilled buyers increase their chances of winning catches with the smallest possible margins.

Another possible explanation for the large buyers' lower prices is

[4] Take the largest buyer as an example. The mean of the fitted price is 8.265 per kilogramme. The sum of coefficients of log(*Transaction-Quantity*) and the interaction terms for buyer 1 is 0.0098 (= − 0.0886 + 0.0984). Taking the shift effect (− 1.510) for buyer 1 into account, the price change following a 10% change in transaction quantity would be about NOK − 1.502 per kilogramme (= 8.265 * (1 + 10%*0.0098%) – 8.265 – 1.510).

[5] The same values of the numeric variables were used to get the fitted prices for the large and small buyers. This may not reflect the differences in preferences between buyers of different sizes.

collusion or bid rigging. Bid rigging is difficult to uncover [18] and the nature of the data makes it difficult to pursue this possibility directly. Simply asking buyers if they collude was not considered appropriate as it would be asking them to admit to illegal business practice. It should be noted, however, that there has not been any coverage in the trade press indicating buyer collusion within the observation period for this study, indicating that bid rigging was not a substantial problem during this period.

5.1. Practical implications

The findings revealed that the largest buyers pay less than other buyers, all other variables being equal, but also that the largest buyers benefit from a greater quantity discount than other buyers. Because of the very high concentration on the buyer side and large traded volumes, the lower prices paid by large buyers imply substantially reduced income for sellers. The sellers (skippers) could try to increase competition by reducing the size of their catches/lots in each auction so that all buyers could bid, but this would lead to poor utilisation of the vessel's capacity. Uncertainty regarding the catch operation means it may also be difficult to determine the actual size of a catch.

The lower prices paid by large buyers may reflect superior access to – and understanding of – information about the auction, including the information about all bids and bidders which are released immediately after an auction has finished. The auction house (owned by the sellers) might want to hold back this information at least until its strategic value to buyers has diminished.

5.2. Suggestions for future research

An interesting avenue for further research would be to explore the relationship between seller behaviour and prices achieved at the pelagic auction, in particular whether sellers vary in the prices they achieve and if so, why. Sellers should also be able to exploit the information provided by the auction house and may vary in their ability to do so. For instance, skippers could slow down or speed up their catch rate depending on the changes in volumes and prices at the auction. Vessels also vary with respect to catch capacity and possession of technology to preserve quality [3] and particular vessels may, over time, have gained a reputation for good quality amongst some buyers, resulting in some buyer being loyal to particular sellers and hence willing to pay higher prices to secure their catches. Exploring such issues might shed further light on the important question of why prices differ between buyers in a seemingly perfectly competitive market such as the Norwegian pelagic auction.

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