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Commodities failing in auctions: The story of unsold cod in Norway

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ABSTRACT

This study addresses how commodities that go unsold at auction perform when they are subsequently sold directly or at auction. Given that the share of unsold commodities is up to 50% in some markets, this is an important yet neglected topic. With a unique dataset including approximately 40,000 frozen Atlantic cod transactions, with detailed information about each lot, including if it was previously withdrawn from the auction, we apply hedonic price modeling to investigate how these lots are priced. The results indicate that when previously withdrawn lots are sold directly, they achieve lower prices than comparable lots. In the auction market, on the other hand, previously unsold lots achieve slightly higher prices than comparable lots.

1. Introduction

In auction markets for commodities, it is not uncommon to fail to sell within the closing time. For example, in a five-year period, 481 out of 1437 forest areas offered for auction by the Quebec Timber Marketing Board were unsold (Rönnqvist et al., 2018), and in French timber auctions, the share of unsold lots can reach 50% (Préget and Waelbroeck, 2012). In the main ex-vessel market for frozen cod in Norway, the focus of this study, about 46% of final transactions involved lots that had previously gone unsold at auction.

These observations give rise to an interesting question with implications for both research and practice – what final prices withdrawn commodities achieve when finally sold. Theoretically, buyers may believe that commodities that go unsold at auction are of lower value than otherwise identical commodities, giving rise to "burning effects" (Ashenfelter, 1989). Such beliefs may arise when buyers are uncertain about the quality of a commodity, and when they have common values. That is, they consider the opinion of other buyers while valuing a commodity, which in the case of unsold commodities is signaled by other buyers' lack of willingness to pay. Studies of auctions for non-commodities such as art and real estate indicate that burning effects are present for withdrawn items when they are later sold directly or through auction. For example, Ashenfelter and Genesove (1992) document that condominium units in New Jersey sold through bilateral negotiation after having gone unsold at auction were sold at a 13% discount. Beggs and Graddy's (2008) study of art auctions at Sotheby's and Christie's in New York and London found that unsold paintings that were sold at the same auction house within two years were sold at a discount of 37% compared to other paintings.

If commodities that were attempted sold at a previous auction are later sold at lower prices than otherwise identical commodities, without the actual quality being lower, it implies a loss for the seller. Burning effects for withdrawn commodities seem likely because uncertainty regarding quality is often a key market feature. For example, Anissa et al. (2021) describe how bulking of smallholder

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output leads to a mixing of high- and low-quality wheat, leading to uncertainty regarding product quality and low prices for all sellers. In the New Bedford fish auction, the fish is sold by the boatload and not sorted by quality, making it difficult for buyers to price high or low quality (Peterson and Georgianna, 1988). In coastal Norway, quality grading of fresh cod catches is costly and generally not conducted, resulting in a lack of quality-based pricing (Sogn-Grundvåg et al., 2021b).

In addition, buyers may value commodities in the same way because they may have similar plans for the purchased commodities (Armstrong, 2001). Due to uncertainty regarding the quality of auctioned fish, buyers/processors may not know what prices they will achieve for the final products. Because they are not sure about the true value of the raw materials, they may rely, at least partly, on other buyers' bids, or lack thereof, as signals about the true value of an auctioned lot. Thus, when a lot fails to sell at auction, buyers may take this as a signal of low quality, leading to burning effects when the seller subsequently tries to sell the lot directly or at the auction.

Surprisingly, but perhaps due to data limitations, we could not find any studies focusing on how commodities having gone unsold at auctions perform when they are later sold directly or re-auctioned. This study aims to fill some of this gap in the literature by using the case of the auction of frozen headed and gutted cod in Norway. To examine the price performance of previously unsold lots when sold later at auction or directly, we apply hedonic price models to a unique dataset containing approximately 40,000 transactions of frozen Atlantic cod from 2011 to 2021. The dataset is unique because of detailed information about each transaction, including observable quality attributes such as the average fish size in each lot, the fishing gear employed, as well as whether a sold lot had previously been withdrawn from the auction. Approximately 37% and 53% of the lots sold in the auction and direct sales markets, respectively, had previously gone unsold at the auction.

Because the two market modes – auction and direct sales – may differ in informational efficiency (Bajari et al., 2009; Sogn-Grundvåg and Zhang, 2021) and the degree of competition (Bulow and Klemperer, 1996), we apply hedonic price models to different sub-samples of the data. More specifically, we compare two sets of models for both the auction and direct sales markets: one for all transactions except previously unsold lots, and the other for lots previously withdrawn from the auction. In this way, we can compare coefficients for the various control variables between the two models for each market mode. This allows us to investigate if withdrawn lots perform differently compared to lots that have not gone unsold at auction.

The remaining part of the paper is organized as follows. Section 2 describes the ex-vessel markets for cod and provides theoretical considerations related to the sale of lots that had previously gone unsold at auction. Section 3 provides a preliminary analysis of the data, and section 4 outlines the hedonic models and descriptive statistics. Section 5 reports the results, and section 6 concludes the study.

2. The ex-vessel markets for cod

The frozen cod included in this study is sold through the Norwegian Fishermen's Sales Organization (NFSO), which has exclusive rights to all ex-vessel sales of cod and other groundfish landed along the northern coasts of Norway.[1] The NFSO is responsible for the auction rules, manages the auction for frozen groundfish such as Atlantic cod, haddock, and saithe, and sets minimum prices for different size classes of different species.

The frozen cod is mainly landed by large oceangoing trawlers, longliners, and demersal seiners (Sogn-Grundvåg et al., 2020). These vessel groups apply different fishing gear, but trawlers and seiners have in common a very large capacity to catch fish in a single haul. This reduces fishing costs but may compromise fish quality (Bertheussen and Dreyer, 2019; Rotabakk et al., 2011; Sogn-Grundvåg et al., 2020). Longliners, on the other hand, take onboard the fish one by one. This makes it possible to bleed and process each fish immediately after catching, which is the main reason for the higher fish quality generally provided by longliners (Rotabakk et al., 2011; Sogn-Grundvåg et al., 2020), leading to higher market prices both at the ex-vessel (Sogn-Grundvåg et al., 2020) and retail (Sogn-Grundvåg et al., 2013, 2014) levels of the value chain.

However, quality variation between catches landed with the same fishing gear may occur. This may be caused by variations in the size of hauls and different onboard processing facilities and routines between vessels fishing with the same gear (Olsen et al., 2014; Rotabakk et al., 2011). Thus, despite being an important observable quality signal (Lee, 2014; McConnell and Strand, 2000; Sogn-Grundvåg et al., 2020), fishing gears may conceal quality variation that are not observable in the auction (Sogn-Grundvåg and Zhang, 2021). For example, large hauls when trawling may affect fish quality negatively, but information about haul sizes is generally not provided in the auction (Sogn-Grundvåg and Zhang, 2021). This implies that the quality of fish may vary among lots with the same observable attributes (Gobillon et al., 2017; Sogn-Grundvåg and Zhang, 2021; Wolff and Asche, 2022).

Catches are landed at independent cold storage plants spread along the coastline, from which buyers ship the lots by cargo vessels to processing plants in Norway or abroad (Bendiksen and Dreyer, 2003), with China being the largest market with processing for re-exports as the main activity (Asche et al., 2022b). The fisher pays a weekly storage fee, but the fish can be stored for several weeks should the fisher anticipate future price increases. However, a longer storage time reduces the quality of cod (Badii and Howell, 2002) and leads to lower prices (Sogn-Grundvåg and Zhang, 2021). The fisher is free to choose between auction and direct sales.[2] The NFSO

[1] Frozen cod landed in the southern and western parts of Norway are sold through the Sunnmøre and Romsdal Fishermen's Sales Organization and Vest-Norges Fiskesalgslag. Most frozen cod is, however, sold through the NFSO.

[2] As of January 1, 2022, the NFSO, along with the two other sales organizations for frozen groundfish, introduced a trial period of one year (2022) wherein each vessel must offer at least 50% of its yearly landings of frozen cod (and saithe) in the auction. A detailed set of rules (in Norwegian) regarding sellers' references prices is found at https://www.rafisklaget.no/rundskriv-list/1-2022.

charges a service fee of 0.69% of the sales value of frozen headed and gutted cod, independent of sales mode.[3] The average share of auction sales for frozen cod was 40.7% for the 11 years covered by this study. Interestingly, there is substantial seller heterogeneity in the choice of sales mode with the share of auction sales varying between 20% and 80% for the top 20 sellers (Sogn-Grundvåg and Zhang, 2021). For the top 20 buyers there is even larger variation in the choice of market mode with some buyers purchasing all cod directly (Sogn-Grundvåg and Zhang, 2021).

The auction is conducted online on the NFSO's auction website, implying that physical inspection of the fish is not possible at the time of bidding (Sogn-Grundvåg et al., 2021a). On the auction website, all participants can see the details of each lot, including the name of the vessel, the fishing gear used, the date and location of landing, a fish quality index (downgraded or not),[4] and the product form. The seller sets a reserve price for the lot in NOK per kilogram, but this is not binding, as about one-third of the auction transactions included in this study were sold at a price below sellers' reserve prices.

The auctioneer puts out lots on the auction website with a fixed closing time, usually the next day. The auction is an English type of auction where the bidder with the highest bid at the closing time wins. If a lot is not sold within the closing time, the lot is withdrawn to be sold later at auction or directly. In the 11-year period covered by this study, 46.4% of all transactions involved products that had previously been withdrawn from the auction.

When a lot fails to sell at auction, sellers must consider trying the auction again or sell directly. Buyers may influence this choice as they can refrain from posting bids in the auction with the aim to avoid competition and purchase the same lot directly as soon as it has gone unsold in the auction. Selling a previously withdrawn lot directly is probably tempting for sellers because it implies no additional storage costs and fast cash-flow. Trying the auction again may be perceived as more uncertain as the lot may go unsold for a second time. However, the actual interest in a withdrawn lot may also influence sellers' choice of sales mode. One of the sellers explained to us that if they get several inquiries or offers for a withdrawn lot, they will try the auction again. This implies that buyers' attempts to avoid the competition in the auction may be futile and that the competition among the interested buyers in a new auction may lead to high prices for the same lot. In fact, in our sample the average number of participating buyers at auctions for previously withdrawn lots was just marginally smaller than for lots that had not gone unsold at the auction, with 2.1 versus 2.4 unique bidders per auction, respectively.

It should be noted that the online auction does not provide buyers with information that a lot has been withdrawn from a previous auction. However, according to the auctioneer, buyers are very well informed and almost always know whether a lot has previously gone unsold at auction. Buyers may also call the auctioneer and ask for more details about lots, including if it has previously been withdrawn from the auction.

3. Data and preliminary analysis

The data include details of 39,414 transactions of frozen headed and gutted Atlantic cod during the period January 2011–December 2021, which includes 636,816 tons of Atlantic cod with a sales value of NOK 16,579 million.[5] The data also includes information about the sales mode (auction or direct sales) and whether lots had been withdrawn from previous auctions. Fig. 1. Shows the structure of the frozen cod market.

For each transaction, the data include the landing date, the name of the vessel and buyer, the weight of the lot in kilograms, the price in NOK per kilogram, the fishing gear (bottom trawl, longline, demersal seine, or other gears), the size group of the fish in kilograms, its quality (regular or downgraded), and so on.

The annual transaction quantities and prices during the sample period varied substantially, as illustrated in Fig. 2, where the intra-annual variation is indexed to 100 in 2011. The figure shows that prices dropped substantially from 2012 to 2013, which was probably caused by large increases in Norwegian cod landings, which rose from 340,000 tons in 2011 to 470,000 tons in 2013.[6] After this, landings averaged almost 400,000 tons, but with a decline towards the end of the sample period. An important reason for the increasing prices between 2013 and 2019 was a weakening of the NOK against key currencies such as the USD and GBP (Nyrud, 2020; Nyrud et al., 2016), which raised cod export prices and the price of frozen cod along the supply chain. The drop in prices in 2020 was probably caused by the widespread social distancing and lockdown measures to contain the spread of the coronavirus during the first phase of the COVID-19 pandemic, strongly affecting the hotel, restaurant, and cantina sector (Asche et al., 2022a).

Fig. 3 shows that the share of auction sales dropped from 2015 to 2017, when more than 60% of all lots were sold directly. The figure also shows that the share of auction deals for withdrawn lots varies between approximately 25% (2020) and 40% (2016), implying that the direct sales market is a more important sales channel for withdrawn lots. Fig. 4 shows that trawling is the primary fishing gear for withdrawn lots, corresponding with the observation that the trawl is the dominant gear in this fishery (see Table 1).

Fig. 5 shows yearly average prices for the sample period for lots having not gone unsold previously and lots previously unsold at

[3] In some auctions, the auctioneer may charge the seller a fee on unsold items to make sure the seller bears some of the cost of auctioning but not selling an item (Ashenfelter, 1989), which increases the transaction costs for unsold lots.

[4] Before offering a lot at auction, sellers may downgrade fish if the quality is low. This is done to avoid costly complaints and to maintain a good reputation (Sogn-Grundvåg and Zhang, 2021).

[5] The sales value is about NOK 23,340 million adjusted by the Norwegian consumer price index of food (2015 = 100) from Statistics Norway.

[6] There is a global market for cod (Asche et al., 2002, 2004; Gordon and Hannesson, 1996; Nielsen, 2005), and as such, Norway's landings cannot explain larger price movements. However, as there is a common quota-setting process in the northeast Atlantic, the quota movements for other important harvesting nations like Russia will be highly correlated with the Norwegian quota.

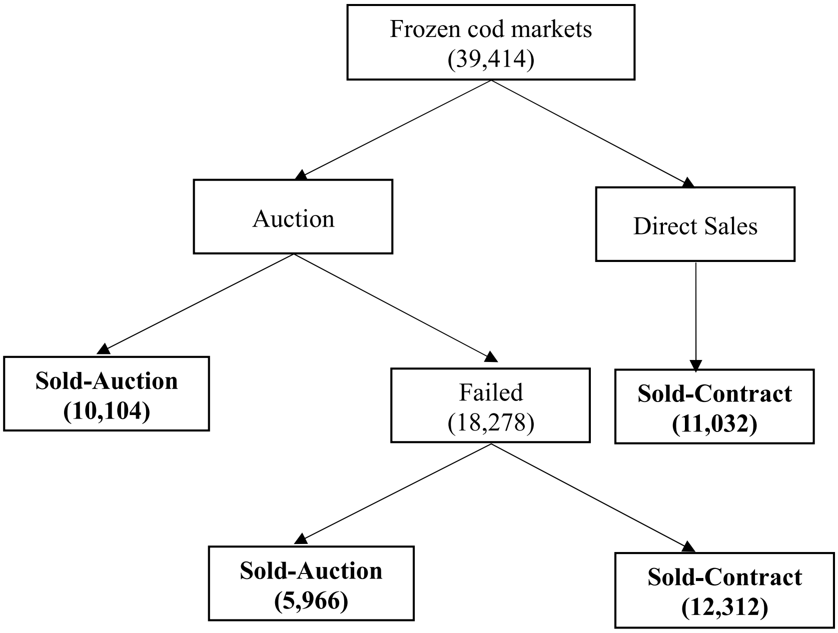

Fig. 1. Frozen cod market modes and the numbers of transactions (in parentheses).

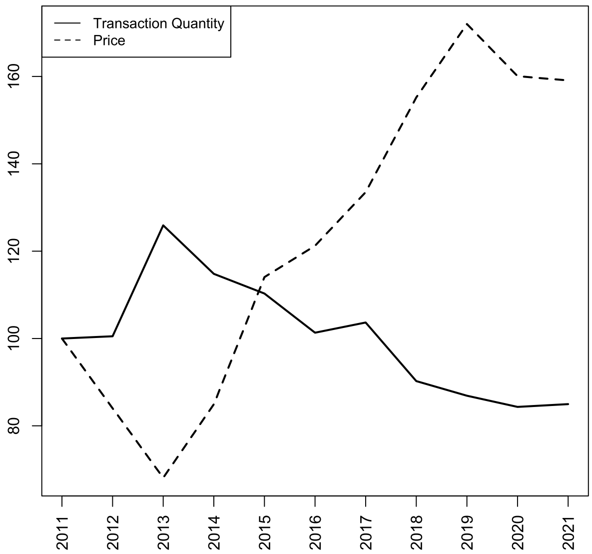

Fig. 2. Indexes of yearly average prices and transaction quantities for 2011–2021 (2011 = 100).

auction by market mode. For most of the period, but especially for the last six years, prices for previously unsold lots in both the auction and direct sales markets were somewhat lower than prices for lots that had not gone unsold in previous auctions. These price differences may be caused by differences in product attributes between sold and previously unsold lots in the two markets. Thus, the hedonic models presented below will estimate prices for sold and withdrawn lots subsequently sold directly or through the auction, while controlling for other price determinants such as fishing gear.

4. Econometric models

Hedonic price models are the most common approach to investigate the price effect of fine-scale product attributes in seafood markets (Asche et al., 2015; Gobillon et al., 2017; Kristofersson and Rickertsen, 2007; McConnell and Strand, 2000), and has also been used to assess quality-based pricing (Sogn-Grundvåg et al., 2021b) and price differences between auction and direct sales markets (Sogn-Grundvåg and Zhang, 2021). Here, we apply seven hedonic price regression models using different samples to examine how

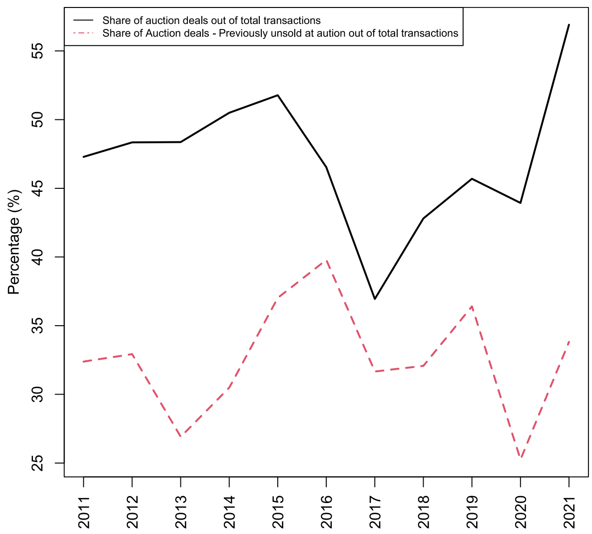

Fig. 3. Share of total auction deals and auction deals - previously unsold at auction out of all transactions by year.

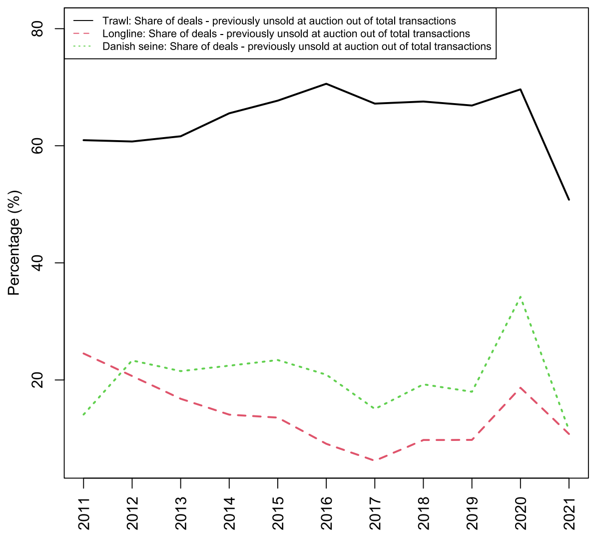

Fig. 4. Share of sold cod that had previously gone unsold out of total transactions by fishing gear and year.

previously unsold cod performs when sold at auction or directly.

Model A includes all transactions in the auction and direct sales markets with three dummies: *PrevUnsold-Auction* for cod that had previously gone unsold at auction, *Sold-Directly* for direct sales but not previously unsold at auction, and *PrevUnsold-Directly* for previously unsold at auction and subsequently sold in the direct sales market, compared to transactions in the auction that had not previously gone unsold in auctions. The baseline model specification is in the form:

$$\log(Price_i) = a_0 + a_1 PrevUnsold\_Auction_i + a_2 Sold\_Directly_i + a_3 PrevUnsold\_Directly_i + \sum\nolimits_{k=1}^{n} b_k X_{k,i} + \sum\nolimits_{k=2}^{11} y_k Year_{k,i} + \sum\nolimits_{k=2}^{12} m_k Month_{k,i} + Residual_i \tag{1}$$

(Model A for full sample)where i represents the number of transactions and log is the logarithm function. The price is in NOK per kilogram for each transaction. The error term, *Residual*, captures any other unobserved factors that might influence the price. X represents a vector of control variables. The yearly and monthly dummies are included in the model to control for any seasonal heterogeneity in prices.

Model A assumes the same impacts of control variables and seasonal dummies on transactions in the auction and direct sales markets. We further investigate the impact of lots that had previously gone unsold in the auction on subsequent prices in the auction and direct sales markets separately. This gives rise to Model B for the auction and Model C for direct sales as follows:

Table 1
Descriptive statistics.

Variable	Model A		Model B		Model C		Model D		Model E		Model F		Model G	
	Whole sample		Subsample for all lots sold at auction		Subsample for all lots sold directly		Subsample for auction deals – not at auction previously		Subsample for auction deals –previously unsold at auction		Subsample for direct sales – not at auction previously		Subsample for direct sales – previously unsold at auction	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Sold-Auction	0.256	0.437	0.629	0.483										
PrevUnsold-Auction	0.151	0.358	0.371	0.483										
Sold-Directly	0.280	0.449			0.473	0.499								
PrevUnsold-Directly	0.312	0.463			0.527	0.499								
Price, log	3.224	0.354	3.237	0.359	3.215	0.350	3.248	0.369	3.219	0.343	3.236	0.361	3.197	0.339
Daily-Quantity, log	13.00	0.96	12.89	0.95	13.08	0.960	12.87	0.98	12.92	0.90	13.03	1.00	13.13	0.92
Transaction-Quantity, log	8.195	2.045	8.010	1.985	8.321	2.076	8.103	1.950	7.853	2.034	8.272	2.127	8.366	2.028
Fish-Size, log	0.967	0.740	1.062	0.746	0.901	0.729	1.075	0.743	1.041	0.751	0.923	0.717	0.881	0.739
Quality-A	0.924	0.265	0.882	0.323	0.953	0.212	0.923	0.267	0.813	0.390	0.954	0.209	0.952	0.214
Storage-Time, log	1.834	1.045	1.842	0.876	1.828	1.147	1.702	0.872	2.079	0.832	1.693	1.254	1.949	1.027
Trawl	0.631	0.482	0.560	0.496	0.680	0.466	0.364	0.481	0.892	0.310	0.471	0.499	0.867	0.339
Longline	0.240	0.427	0.262	0.440	0.225	0.418	0.388	0.487	0.049	0.216	0.386	0.487	0.081	0.273
Demersal-Seine	0.100	0.300	0.142	0.349	0.072	0.258	0.196	0.397	0.050	0.218	0.106	0.308	0.041	0.199
Buyer-Quantile 1	0.008	0.087	0.008	0.088	0.007	0.086	0.007	0.084	0.009	0.095	0.009	0.094	0.006	0.079
Buyer-Quantile 2	0.027	0.162	0.043	0.203	0.016	0.126	0.044	0.205	0.041	0.198	0.017	0.131	0.015	0.121
Buyer-Quantile 3	0.100	0.299	0.113	0.317	0.090	0.286	0.107	0.309	0.124	0.330	0.095	0.294	0.085	0.279
Buyer-Quantile 4	0.866	0.341	0.836	0.371	0.886	0.317	0.842	0.365	0.826	0.379	0.878	0.327	0.894	0.308
Seller-Quantile 1	0.031	0.173	0.042	0.200	0.023	0.151	0.056	0.230	0.018	0.132	0.033	0.179	0.014	0.119
Seller-Quantile 2	0.078	0.268	0.101	0.302	0.061	0.240	0.134	0.341	0.046	0.210	0.082	0.275	0.043	0.202
Seller-Quantile 3	0.211	0.408	0.240	0.427	0.191	0.393	0.325	0.468	0.095	0.293	0.269	0.443	0.121	0.326
Seller-Quantile 4	0.681	0.466	0.617	0.486	0.725	0.447	0.485	0.500	0.841	0.365	0.616	0.486	0.822	0.382
Pair-Quantile 1	0.059	0.236	0.100	0.300	0.031	0.174	0.110	0.312	0.083	0.276	0.029	0.169	0.033	0.178
Pair-Quantile 2	0.095	0.294	0.156	0.363	0.054	0.225	0.192	0.394	0.095	0.294	0.044	0.206	0.062	0.241
Pair-Quantile 3	0.164	0.370	0.238	0.426	0.113	0.317	0.256	0.436	0.207	0.405	0.113	0.317	0.113	0.317
Pair-Quantile 4	0.682	0.466	0.507	0.500	0.802	0.398	0.443	0.497	0.615	0.487	0.813	0.390	0.793	0.405
Price, NOK/kg	26.652	8.690	27.065	9.137	26.367	8.357	27.45	9.508	26.42	8.435	27.00	8.703	25.80	7.992
Daily-Quantity, kg	638,256	546,134	561,889	437,136	690,826	604,379	557,998	434,294	568,479	441,866	678,140	640,105	702,194	570,257
Transaction-Quantity, kg	16,157	29,194	13,204	24,111	18,190	32,073	13,284	22,596	13,068	26,482	17,818	31,381	18,523	32,678
Fish-Size, kg	3.368	2.236	3.689	2.353	3.147	2.123	3.735	2.426	3.611	2.222	3.196	2.155	3.102	2.093
Storage-Time, days	11.80	20.92	10.38	18.59	12.77	22.33	9.08	16.53	12.59	21.45	12.56	23.53	12.95	21.19

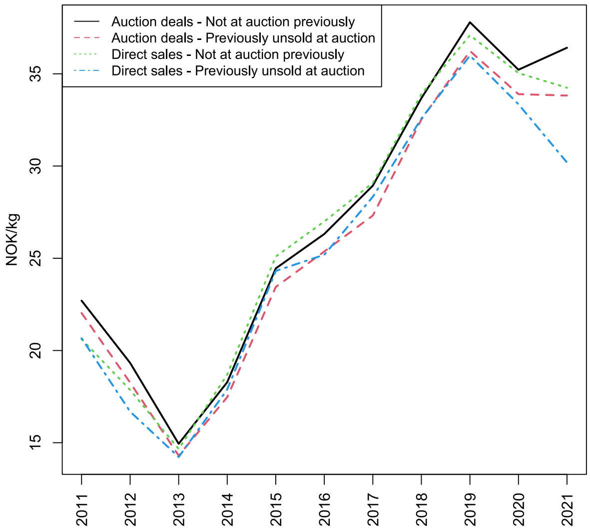

Fig. 5. Yearly average prices in the auction and direct sales markets for sold and previously unsold lots.

$$\log(Price_i) = a_0 + a_1 PrevUnsold\_Auction_i + \sum\nolimits_{k=1}^{n} b_k X_{k,i} + \sum\nolimits_{k=2}^{11} y_k Year_{k,i} + \sum\nolimits_{k=2}^{12} m_k Month_{k,i} + Residual_i \tag{2}$$

(Model B for auction deals)

$$\log(Price_i) = a_0 + a_3 PrevUnsold\_Directly_i + \sum\nolimits_{k=1}^{n} b_k X_{k,i} + \sum\nolimits_{k=2}^{11} y_k Year_{k,i} + \sum\nolimits_{k=2}^{12} m_k Month_{k,i} + Residual_i \tag{3}$$

(Model C for direct sales)

Models B and C assume, for either auction or direct sales, the same impacts of control variables and seasonal dummies on deals that have not gone unsold at auction and deals previously unsold at auction. Finally, we estimate the price differences in deals that have not gone unsold at auction and previously unsold lots at auction, for auction or direct sales, using the following specification:

$$\log(Price_i) = a_0 + \sum\nolimits_{k=1}^{n} b_k X_{k,i} + \sum\nolimits_{k=2}^{9} y_k Year_{k,i} + \sum\nolimits_{k=2}^{11} m_k Month_{k,i} + Residual_i \tag{4}$$

(Model D for Auction deals – Not at auction previously, Model E for Auction deals – Previously unsold at auction, Model F for Direct sales – Not at auction previously, and Model G for Direct sales – Previously unsold at auction.

Following previous literature (Asche et al., 2015; Fluvià et al., 2012; Gobillon et al., 2017; Lee, 2014; Pettersen and Asche, 2020; Sogn-Grundvåg and Zhang, 2021), the control variables (X) include the average size of the cod *(Fish-Size)*,[7] fish quality (*Quality-A*), storage time (*Storage-Time*), dummies for fishing gear (*Trawl*, *longline*, and Demersal-*Seine*), total daily transaction quantity (*Daily--Quantity*), and transaction quantity (*Transaction-Quantity*).

The heterogeneity of buyers, sellers, and buyer–seller pairs may influence prices (Gobillon et al., 2017; Oglend et al., 2022; Pettersen and Asche, 2020; Sogn-Grundvåg and Zhang, 2021; Wolff and Asche, 2022). Accordingly, we set quantile dummies for buyers, sellers, and buyer–seller pairs with respect to transaction quantities for the sample period. For example, we aggregate transaction quantities for buyers and create dummies for buyers in the different quantile groups: *Buyer-Quantile* 2, *Buyer-Quantile* 3, and *Buyer--Quantile* 4, with the buyers with the smallest quantities (*Buyer-Quantile* 1) as the base.

Because the different models use different datasets, descriptive statistics for the variables in all seven models are presented in Table 1. Under the dummy-coding technique, the reported mean for each dummy variable is the number of observations (transactions) within each category as a proportion of the total number of observations. Model A uses the full dataset, and thus it can be calculated from Table 1 that 40.7% (0.256 for *Sold-Auction* + 0.151 for *PrevUnsold-Auction*) of all transactions were conducted in the auction market. Surprisingly, as many as 46.3% (0.151 for *PrevUnsold-Auction* + 0.312 for *PrevUnsold-Directly*) of transactions involved products that had previously gone unsold at auction. For Models B and C, 37.1% and 52.7% of all transactions in the auction and direct sales markets, respectively, involved products that had previously gone unsold at auction. Table 1 also shows that for Model A, the trawl was the dominant fishing gear, accounting for about 63.1% of all transactions during the sample period, followed by longline (24%) and demersal seine (10%). Moreover, in 92.4% of all transactions, the cod was classified by the seller to be of regular quality (*Quality-A*), with downgraded cod as the base.

[7] We changed the various size categories in the data to average weights rather than using dummies for size categories in the econometric analysis. For example, the category between "1 and 2.5 kg" was changed to 1.75 kg. We prefer this approach because there are several different size categories in the data, which would mean many dummies in the models. In addition, some of the original size categories are somewhat poorly specified, such as "more than 0.8 kg" The conversions were done together with staff from the NFSO. For example, "more than 0.8 kg" was changed to 1.6 kg.

An interesting observation from Table 1 is that the share of trawler-caught cod is much higher for previously unsold cod than sold cod for both market modes. In the auction, the share of trawler caught cod is 36.4% for sold cod (Model D) and 89.2% for previously unsold cod (Model E). In the direct sales market, the share of trawler-caught cod is 47.1% for sold cod (Model F) and 86.7% for previously unsold cod (Model G). In addition, the share of cod caught with longline drops to almost zero for previously unsold from 38.8% to 38.6% for sold cod in the auction and direct sales markets, respectively. These observations indicate that cod of high quality is easier to sell first time in the auction than cod of lower quality. They may also explain the lower mean prices for previously withdrawn lots in both market modes compared to lots that had not gone unsold. The average price for sold auction lots is 3.89% higher than the price for previously withdrawn lots subsequently sold in the auction (NOK 27.45 per kilo in the subsample for Model D versus NOK 26.42 per kilo in the subsample for Model E). For direct sales, the average price for sold lots is 4.65% higher than the price for previously withdrawn lots (NOK 27.00 per kilo in the subsample for Model F versus NOK 25.80 per kilo in the subsample for Model G).

Table 2

Estimation results for Models A for whole sample, B for all lots sold at auction, and C for all lots sold directly. (Dependent variable: log (Price)).

Variable	Whole sample	Subsample for all lots sold at auction	Subsample for all lots sold directly
	Model A	Model B	Model C
Intercept	2.5313***	2.5827***	2.4901***
	[0.0223]	[0.0281]	[0.0314]
PrevUnsold-Auction	0.004*	0.0061**	
	[0.0023]	[0.0027]	
Sold-Directly	−0.0188***		
	[0.0019]		
PrevUnsold-Directly	−0.036***		−0.0168***
	[0.002]		[0.0018]
Quantity-Daily, log	−0.0003	0.0026**	−0.0022**
	[0.0008]	[0.0013]	[0.001]
Transaction-Quantity, log	0.0021***	0.0029***	0.0018***
	[0.0003]	[0.0006]	[0.0004]
Fish-Size, log	0.1083***	0.1073***	0.1074***
	[0.0009]	[0.0014]	[0.0011]
Quality-A	0.2583***	0.2421***	0.276***
	[0.004]	[0.0045]	[0.0072]
Storage-Time, log	−0.0183***	−0.02***	−0.0174***
	[0.0007]	[0.0014]	[0.0008]
Trawl	0.0449***	0.0344***	0.0521***
	[0.0044]	[0.0054]	[0.007]
Longline	0.1058***	0.0957***	0.1143***
	[0.0044]	[0.0053]	[0.007]
Demersal-Seine	−0.0165***	−0.0242***	−0.008
	[0.0048]	[0.0058]	[0.0077]
Buyer-Quantile 2	0.0908***	0.0472**	0.0948***
	[0.0188]	[0.0205]	[0.0287]
Buyer-Quantile 3	0.1768***	0.1173***	0.2000***
	[0.018]	[0.0199]	[0.027]
Buyer-Quantile 4	0.184***	0.1342***	0.1991***
	[0.018]	[0.0198]	[0.0269]
Seller-Quantile 2	0.006	0.0241***	−0.0145**
	[0.0045]	[0.0062]	[0.0067]
Seller-Quantile 3	0.0157***	0.0431***	−0.0152**
	[0.0042]	[0.0058]	[0.006]
Seller-Quantile 4	0.0024	0.0363***	−0.0317***
	[0.0042]	[0.0059]	[0.0059]
Pair-Quantile 2	0.0148***	0.009**	0.0262***
	[0.0041]	[0.0045]	[0.0088]
Pair-Quantile 3	0.0096**	−0.0009	0.0238***
	[0.0039]	[0.0044]	[0.0081]
Pair-Quantile 4	0.0171***	−0.0046	0.0388***
	[0.0039]	[0.0046]	[0.0079]
Dummy for years	Yes	Yes	Yes
Dummy for months	Yes	Yes	Yes
Adj. R^2	0.8796	0.8803	0.8839
obs.	39,414	16,070	23,344

Notes: ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively. Robust standard errors are in brackets.Model A: $\log(Price_i) = a_0 + a_1 PrevUnsold\_Auction_i + a_2 Sold\_Directly_i + a_3 PrevUnsold\_Directly_i + \sum_{k=1}^{n} b_k X_{k,i} + \sum_{k=2}^{11} y_k Year_{k,i} + \sum_{k=2}^{12} m_k Month_{k,i} + Residual_i$.Model B: $\log(Price_i) = a_0 + a_1 PrevUnsold\_Auction_i + \sum_{k=1}^{n} b_k X_{k,i} + \sum_{k=2}^{11} y_k Year_{k,i} + \sum_{k=2}^{12} m_k Month_{k,i} + Residual_i$;Model C: $\log(Price_i) = a_0 + a_3 PrevUnsold\_Directly_i + \sum_{k=1}^{n} b_k X_{k,i} + \sum_{k=2}^{11} y_k Year_{k,i} + \sum_{k=2}^{12} m_k Month_{k,i} + Residual_i$

The average fish size is not substantially different between sold lots and withdrawn lots for both the auction and direct sales markets. But the share of regular quality is higher for sold lots compared to withdrawn lots when sold at auction (Model D versus Model E). There is also a difference in average storage time between lots sold and withdrawn lots when these are sold in the auction (9.08 versus 12.59 days, respectively). For direct sales, the difference in storage time is very small between sold and withdrawn lots.

Table 1 also shows the share of transactions for different buyer, seller, and pair quantiles based on traded quantity, as noted above. For Model A with the full sample, the smallest buyers categorized in *Buyer-Quantile* 1 accounted for less than 1% of all transactions, and *Buyer-Quantile* 4 accounted for more than 86.6% of transactions. The quantile for the sellers and buyer–seller pairs with the largest traded quantity accounted for 68% of transactions.

5. Results

As described above, all seven models use different datasets, with Model A using the full dataset and the remaining models using subsets of the whole sample. The results are presented in Tables 2–4. The adjusted R^2 values are between 0.876 and 0.894 for the models, indicating very good fit with the data. We first consider the coefficients of the dummies for previously unsold lots in Models A, B, and C.

Table 3
Estimation results for Models D for Auction deals – Not at auction previously and Model E for Auction deals – Previously unsold at auction. (Dependent variable: log (Price)).

Variable	Subsample for auction deals – not at auction previously	Subsample for auction deals – previously unsold at auction
	Model D	Model E
Intercept	2.5506***	2.6247***
	[0.0377]	[0.0465]
Quantity-Daily, log	0.0033**	0.0001
	[0.0016]	[0.0022]
Transaction-Quantity, log	0.0042***	0.0005
	[0.0007]	[0.0009]
Fish-Size, log	0.1171***	0.0916***
	[0.0019]	[0.0023]
Quality-A	0.2445***	0.2532***
	[0.0075]	[0.0057]
Storage-Time, log	−0.0118***	−0.0317***
	[0.0017]	[0.0026]
Trawl	0.0266***	0.0639***
	[0.0058]	[0.0178]
Longline	0.0916***	0.1334***
	[0.0056]	[0.0191]
Demersal-Seine	−0.0242***	−0.0082
	[0.0061]	[0.0196]
Buyer-Quantile 2	0.0443	0.0533*
	[0.0282]	[0.0291]
Buyer-Quantile 3	0.1247***	0.1015***
	[0.0276]	[0.0274]
Buyer-Quantile 4	0.1321***	0.1300***
	[0.0276]	[0.0273]
Seller-Quantile 2	0.0273***	0.0096
	[0.0063]	[0.021]
Seller-Quantile 3	0.0419***	0.0438**
	[0.006]	[0.0204]
Seller-Quantile 4	0.033***	0.0448**
	[0.0061]	[0.021]
Pair-Quantile 2	0.0105**	0.0016
	[0.005]	[0.0093]
Pair-Quantile 3	−0.0006	−0.0022
	[0.005]	[0.0088]
Pair-Quantile 4	−0.0085	0.0018
	[0.0053]	[0.0093]
Dummy for years	Yes	Yes
Dummy for months	Yes	Yes
Adj. R^2	0.8858	0.8757
obs.	10,104	5966

Notes: ***, **, and * indicate significance at the 0.01, 0.05 and 0.10 level, respectively. Robust standard errors are in brackets. Model specification: $\log(Price_i) = a_0 + \sum_{k=1}^{n} b_k X_{k,i} + \sum_{k=2}^{9} y_k Year_{k,i} + \sum_{k=2}^{11} m_k Month_{k,i} + Residual_i$.

5.1. Estimates of dummies for lots previously unsold at auction in models A, B, and C

The results for Model A presented in Table 2 show that the coefficient of the dummy for withdrawn lots when later sold at auction (base: sold at auction, not previously withdrawn from the auction) is significant and positive. This indicates that lots that have previously gone unsold at auction achieve a higher price than otherwise comparable lots when later sold at auction, but the price premium for previously unsold cod is only about 0.4%. The dummy for previously withdrawn lots in the direct sales market is significant ($p < 0.01$) and negative. This indicates that lots that have gone unsold in previous auctions are subsequently sold directly at a discount of about −3.6% compared to the base. Model A also contains a dummy variable for direct sales, which is significant ($p < 0.01$) and negative, indicating that auctioned lots achieve 1.88% higher prices than lots sold directly, holding other variables constant.

To examine whether the previously withdrawn lots perform differently in the auction and direct sales markets, we now consider models B and C based on two different subsets of the whole sample. Model B is based on all transactions in the auction, including lots that have previously gone unsold at auction. Here, the estimate for the dummy for previously unsold lots is significant ($p < 0.05$) and positive, but the magnitude is only about 0.61%. Model C is based on all direct sales, including lots previously withdrawn from the auction and later sold directly. As in Model A, the estimate for the dummy for previously unsold lots is significant ($p < 0.01$) and negative, with a magnitude of −1.68%, corresponding to a total effect of NOK 8.2 million for the whole sample period. Despite of this loss for sellers, a larger quantity of previously unsold cod is sold directly than through the auction as shown in Fig. 4.

Table 4
Estimation results for Model F for Direct sales – Not at auction previously, and Model G for Direct sales – Previously unsold at auction. (Dependent variable: log (Price)).

Variable	Subsample for direct sales – not at auction previously	Subsample for direct sales – previously unsold at auction
	Model F	Model G
Intercept	2.4537***	2.5479***
	[0.0463]	[0.0365]
Quantity-Daily, log	−0.0063***	0.0023**
	[0.0015]	[0.0012]
Transaction-Quantity, log	0.0012**	0.0023***
	[0.0006]	[0.0005]
Fish-Size, log	0.11***	0.1034***
	[0.0018]	[0.0015]
Quality-A	0.2687***	0.2853***
	[0.0119]	[0.0084]
Storage-Time, log	−0.015***	−0.0199***
	[0.0011]	[0.0011]
Trawl	0.0551***	0.0273**
	[0.0085]	[0.0138]
Longline	0.1187***	0.0964***
	[0.0082]	[0.0141]
Demersal-Seine	0.003	−0.0585***
	[0.0094]	[0.0148]
Buyer-Quantile 2	0.1563***	−0.0007
	[0.0427]	[0.0333]
Buyer-Quantile 3	0.2533***	0.1116***
	[0.0409]	[0.0303]
Buyer-Quantile 4	0.2484***	0.1155***
	[0.0411]	[0.0303]
Seller-Quantile 2	−0.0148**	−0.0089
	[0.0076]	[0.0123]
Seller-Quantile 3	−0.0156**	−0.005
	[0.0067]	[0.0118]
Seller-Quantile 4	−0.0325***	−0.0197*
	[0.0065]	[0.0117]
Pair-Quantile 2	0.0488***	0.009
	[0.0159]	[0.0103]
Pair-Quantile 3	0.0483***	0.0009
	[0.0142]	[0.0096]
Pair-Quantile 4	0.0686***	0.0086
	[0.0141]	[0.0095]
Dummy for years	Yes	Yes
Dummy for months	Yes	Yes
Adj. R^2	0.8769	0.8943
obs.	11,910	12,426

Notes: ***, **, and * indicate significance at the 0.01, 0.05 and 0.10 level, respectively. Robust standard errors are in brackets. Model specification: $\log(Price_i) = a_0 + \sum_{k=1}^{n} b_k X_{k,i} + \sum_{k=2}^{9} y_k Year_{k,i} + \sum_{k=2}^{11} m_k Month_{k,i} + Residual_i$.

5.2. Estimates of control variables in models A, B, and C

Model A, like all the other models, contains several control variables, most of which are significant. The control variables in models B and C are mostly significant and not very different from those in Model A. Next, we interpret the estimation results using Model A as an example.

For Model A, the only non-significant variable is the numerical variable *Daily-Quantity*. As expected, the variables *Fish-Size* and *Quality-A* (versus downgraded) affect prices positively. *Storage-Time* has a negative effect on prices, which is reasonable given that longer storage time reduces fish quality. The three main types of fishing gear affect prices as expected due to their different effects on fish quality, with longlines generally providing the best fish quality and achieving the highest prices (Sogn-Grundvåg et al., 2020).

The buyer quantiles, with the base group being the smallest buyers in terms of purchased quantity and *Buyer-Quantile 4* representing the buyers with the largest quantities, are all significant and positive in Model A. The results indicate that the largest buyers pay 18.4% higher prices than the smallest buyers, holding other variables constant. The seller- and pair-quantile dummies are also significant, but the magnitudes are small.

The Appendix shows the estimates of the yearly and monthly dummies. The year dummies, with 2011 as the base, are all significant in Model A and show large price variation over time. The month dummies in Model A are all significant and show some seasonal price variation, with the highest prices in October–December.

5.3. Model D versus model E for auction

To refine our analysis of how previously withdrawn lots perform in the auction (or direct sales market; see the next subsection), we compare two models. Models D and E are based on a subset of the data containing auction sales only, with Model D including lots that were not previously unsold at auction and Model E only including previously unsold cod. In this way, we can compare coefficients for the various control variables between the two models to investigate if attribute prices are different for previously unsold lots than comparable lots not previously withdrawn from the auction. This procedure is preferable to using interaction terms because the number of control variables here is so large. The results are shown in Table 3.

Comparing the estimates for Models D and E in Table 3 indicates that the magnitude of coefficients for several variables related to fish quality, such as *Quality-A*, *Trawl*, and *Longline*, are larger for previously unsold lots (Model E). The coefficient of *Fish-Size* for previously unsold cod in Model E is marginally smaller than that in Model D. It can also be seen that the coefficient of *Storage-Time* decreases from −0.012 in Model D to −0.032 in Model E. However, the average storage time in days is about the same for Models D and E (see Table 1). The two models provide different estimates for *Buyer-Quantile 2*, which is significant in Model E and insignificant in Model D, while the opposite is true for *Seller-Quantile 2*.

An interesting result from comparing Models D and E is the different pattern of changes in year dummies reported in the Appendix, which are all significant. The coefficients of the year dummies represent yearly price premiums/discounts compared to the price in the base year (2011), holding the influence on price of other variables constant. The estimated yearly price premiums/discounts are different from the actual yearly prices presented in Fig. 4. The differences in actual prices may mask differences in attributes in different years, while the estimated yearly price premiums/discounts have the advantage that any yearly differences in fish quality, fishing gear, the size of lots, seasonality, and so on are controlled for. After setting the price in the base year to 100, we obtain a price index for the sample period, shown in Fig. 6.

Inspection of Fig. 6 shows that yearly price movements are substantial, with a drop in prices between 2012 and 2013 followed by a steady increase until 2019 and a new but smaller drop in prices in the pandemic years of 2020 and 2021. Moreover, previously unsold lots achieve higher prices than sold lots relative to their respective bases (2011) for most years, especially for the last three years of the sample period. The Appendix shows that, relative to their respective bases, previously unsold lots earn better yearly average prices than sold lots for all years except 2012 and 2016. This indicates that previously unsold lots perform better than sold lots in the auction market.

5.4. Model F versus model G for direct sales

Models F and G are based on a subset of the data containing direct sales only, with Model F including lots that were not previously unsold at auction and Model G only including previously unsold cod. Comparing control variables between the two models indicates that the coefficients for the dummies for trawl and longline are smaller in Model G than in Model F. An interesting difference between the models is that the coefficients for buyer quantiles change substantially. More specifically, in Model F, without previously unsold lots, the smallest buyers (*Buyer-Quantile 1*, the base) pay substantially lower prices than larger buyers, but for previously unsold lots (Model G), the difference is much smaller. In fact, *Buyer-Quantile 2* is only significant in Model G, and the coefficients for *Buyer-Quantiles 3* and *4* are much smaller in Model G than in Model F.

Regarding the yearly dummies in models F and G, all except the dummy for the year 2011 in Model G are significant (see the Appendix). For all years and compared to their respective bases (2011), price estimates are lower for previously unsold lots, holding other variables constant. Fig. 7 illustrates the differences. The Appendix shows that, relative to their respective bases, sold lots earn better yearly average prices than previously unsold lots for all years, holding other variables constant. This indicates that previously unsold lots perform poorer than sold lots in the direct sales market, contrary to the findings for the auction market.

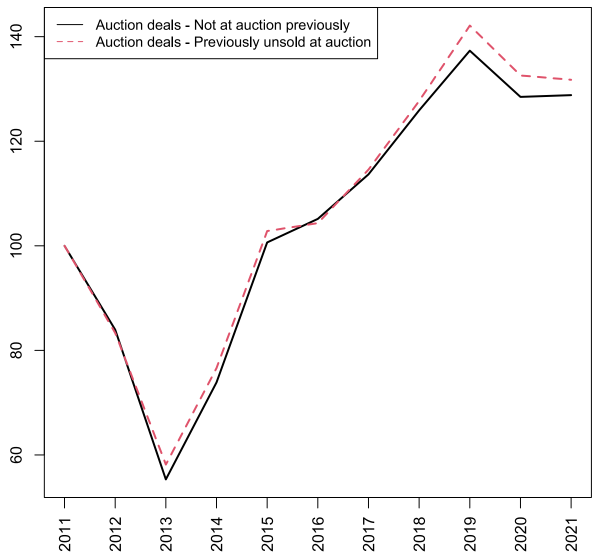

Fig. 6. Price index for auction deals – Not at auction previously and auction deals – Not at auction previously based on the estimated yearly dummies from Models D and E.

6. Conclusion

In the main ex-vessel market for frozen cod in Norway, about 46% of transacted lots had previously been withdrawn from the auction. That a commodity may go unsold in an auction seems to be quite common, although there is limited description of such cases in the literature. How the withdrawn commodities perform when subsequently sold through auction or directly have not been addressed in the past literature focusing on commodity markets. In this study, we investigate what prices lots of frozen cod that was previously withdrawn from the auction achieve when finally sold in new auctions or directly. In doing so, we lean on the burning effects hypothesis that has received some attention in the context of non-commodities such as art and housing (Ashenfelter, 1989; Ashenfelter and Genesove, 1992; Beggs and Graddy, 2008). We apply a series of different hedonic price functions to examine how withdrawn lots of cod in Norway are priced.

Somewhat surprisingly, the results indicate that in the auction market, previously withdrawn lots achieve marginally higher (0.61%) prices than comparable lots that have not previously gone unsold at auction. This is an indication that burning effects are not present for previously unsold lots in the auction market. The price difference, albeit very small, may at least partly be explained by the

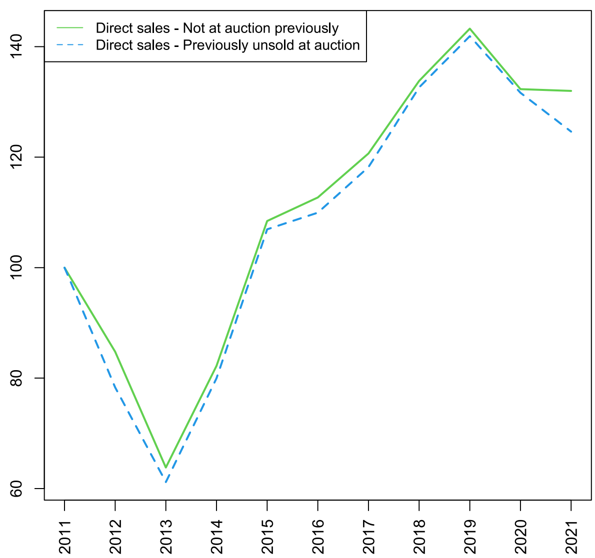

Fig. 7. Price index of Direct sales – Not at auction previously and Direct sales – Not at auction previously based on the estimated yearly dummies from Models F and G.

interest shown by some buyers for some of the withdrawn lots, leading some sellers to put these lots out for a new auction. Because the estimation control for the influence of observable attributes on prices, it is also possible that the previously withdrawn lots have some favorable but unobservable characteristics compared to lots put out for auction for the first time.

For the direct sales market, where 67.4% of the previously unsold lots are traded, burning effects may be present as the results indicate lower prices (−1.66%) for previously withdrawn lots compared to otherwise similar lots that had not gone unsold in the auction. This amounts to NOK 8.2 million for the whole sample period, indicating scientific significance. It is, however, also possible that the lower prices reflect actual quality differences. Because the hedonic models control for the influence of observable attributes on prices, the price difference may be explained by some unobservable quality differences.

Credit author statement

Geir Sogn-Grundvåg: Conceptualization, Investigation, Writing – original draft, Writing- Reviewing and Editing, Project administration, Funding acquisition. Dengjun Zhang: Conceptualization, Methodology, Formal analysis, Investigation, Writing- Reviewing and Editing.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix

Table A
Estimates of yearly and monthly dummies.

Variable	Whole sample	Subsample for all lots sold at auction	Subsample for all lots sold directly	Subsample for auction deals – not at auction previously	Subsample for auction deals – previously unsold at auction	Subsample for direct sales – not at auction previously	Subsample for direct sales – previously unsold at auction
	Model A	Model B	Model C	Model D	Model E	Model F	Model G
2012	−0.1643***	−0.1511***	−0.1716***	−0.1487***	−0.1549***	−0.1404***	−0.205***
	[0.0048]	[0.0069]	[0.0063]	[0.0085]	[0.012]	[0.0095]	[0.008]
2013	−0.3756***	−0.414***	−0.3526***	−0.4241***	−0.3958***	−0.3393***	−0.3655***
	[0.0035]	[0.0048]	[0.0046]	[0.0058]	[0.009]	[0.0074]	[0.0054]
2014	−0.1612***	−0.1997***	−0.1369***	−0.2085***	−0.181***	−0.1251***	−0.1475***
	[0.0039]	[0.0056]	[0.0051]	[0.0066]	[0.0103]	[0.0083]	[0.0062]
2015	0.1317***	0.0934***	0.1578***	0.0876***	0.1094***	0.1656***	0.1506***
	[0.0033]	[0.0045]	[0.0043]	[0.0055]	[0.008]	[0.007]	[0.005]
2016	0.1906***	0.1518***	0.2192***	0.1583***	0.1502***	0.2338***	0.2063***
	[0.0032]	[0.0045]	[0.0043]	[0.0057]	[0.0079]	[0.0068]	[0.0051]
2017	0.281***	0.2466***	0.3012***	0.2434***	0.2526***	0.3135***	0.2888***
	[0.0032]	[0.0043]	[0.0043]	[0.0054]	[0.0079]	[0.0068]	[0.0049]
2018	0.4402***	0.3971***	0.4645***	0.391***	0.409***	0.4697***	0.4582***
	[0.0032]	[0.0046]	[0.0042]	[0.0057]	[0.0081]	[0.0067]	[0.0049]
2019	0.5558***	0.5339***	0.5677***	0.5153***	0.5634***	0.5748***	0.5612***
	[0.0032]	[0.0045]	[0.0042]	[0.0055]	[0.008]	[0.0067]	[0.0048]

(*continued on next page*)

Table A (*continued*)

Variable	Whole sample	Subsample for all lots sold at auction	Subsample for all lots sold directly	Subsample for auction deals – not at auction previously	Subsample for auction deals – previously unsold at auction	Subsample for direct sales – not at auction previously	Subsample for direct sales – previously unsold at auction
	Model A	Model B	Model C	Model D	Model E	Model F	Model G
2020	0.487***	0.4728***	0.496***	0.4585***	0.4995***	0.4968***	0.4902***
	[0.0039]	[0.006]	[0.0049]	[0.0074]	[0.0106]	[0.008]	[0.0058]
2021	0.4496***	0.4481***	0.4402***	0.4417***	0.471***	0.4734***	0.3997***
	[0.0035]	[0.0048]	[0.0048]	[0.0057]	[0.0094]	[0.0072]	[0.0059]
January	−0.092***	−0.0995***	−0.0857***	−0.0968***	−0.1044***	−0.0844***	−0.0853***
	[0.0028]	[0.0047]	[0.0035]	[0.0058]	[0.008]	[0.0049]	[0.0051]
February	−0.0893***	−0.0933***	−0.0802***	−0.0976***	−0.0905***	−0.0962***	−0.0653***
	[0.0032]	[0.0055]	[0.004]	[0.0069]	[0.009]	[0.0058]	[0.0055]
March	−0.1058***	−0.1321***	−0.0837***	−0.1277***	−0.1401***	−0.081***	−0.0823***
	[0.0036]	[0.0058]	[0.0045]	[0.0071]	[0.01]	[0.0066]	[0.0062]
April	−0.0918***	−0.1101***	−0.0784***	−0.1199***	−0.0966***	−0.0846***	−0.0719***
	[0.0033]	[0.0054]	[0.004]	[0.0067]	[0.0096]	[0.0059]	[0.0055]
May	−0.0704***	−0.0751***	−0.0692***	−0.0869***	−0.0547***	−0.069***	−0.072***
	[0.0031]	[0.005]	[0.0038]	[0.006]	[0.0089]	[0.006]	[0.0051]
June	−0.0627***	−0.0708***	−0.0554***	−0.071***	−0.0685***	−0.0516***	−0.0599***
	[0.0029]	[0.0051]	[0.0036]	[0.0064]	[0.0084]	[0.0054]	[0.0048]
July	−0.0561***	−0.0785***	−0.0407***	−0.0772***	−0.0822***	−0.0374***	−0.0412***
	[0.0029]	[0.005]	[0.0036]	[0.0063]	[0.0085]	[0.0055]	[0.005]
August	−0.0334***	−0.0545***	−0.0167***	−0.0612***	−0.0469***	−0.0158***	−0.0175***
	[0.0029]	[0.0049]	[0.0035]	[0.0062]	[0.0081]	[0.0054]	[0.0047]
September	−0.0279***	−0.0328***	−0.0237***	−0.0265***	−0.045***	−0.033***	−0.0139***
	[0.0031]	[0.0049]	[0.0041]	[0.0061]	[0.0085]	[0.0066]	[0.0049]
October	−0.0026	−0.0094**	0.0021	−0.0079	−0.0124	0.0123**	−0.0056
	[0.0029]	[0.0046]	[0.0036]	[0.0055]	[0.0084]	[0.0051]	[0.0051]
November	0.009***	0.0112**	0.0085***	0.0155***	0.0034	0.0177***	−0.0022
	[0.0026]	[0.0044]	[0.0032]	[0.0052]	[0.0081]	[0.0044]	[0.0047]

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