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ARTICLE

Starting high or low in English auctions? The case of frozen saithe in Norway

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Abstract

This study investigates the role of starting prices in sequentially ascending (English) auctions. Applying binary logit and hedonic price models on a unique data set comprising 8217 auctioned lots of frozen saithe, an important species in Norwegian fisheries, we find support for three hypotheses; that low starting prices will lead to a higher share of successful auctions, a higher number of participating bidders, and higher final prices. These results indicate that starting prices in English auctions are important for both seller revenue and auction efficiency and are important with respect to strategic behavior in auction markets for food commodities.

KEYWORDS

ascending auctions, efficiency, seafood commodity, starting price

JEL CLASSIFICATION

D44, L1

1 | INTRODUCTION

The supply of food commodities is often uncertain due to unpredictable climatic and weather conditions. In addition, natural variations in quality may lead to buyer uncertainty regarding the product's value (Anderson & Anderson, 1991; Sogn-Grundvåg & Zhang, 2023a). These factors may explain why auctions are used extensively to establish prices for food commodities around the world. For instance, auctions are found at wholesale markets for fish (Brendstrup & Paarsch, 2006; Fluvià et al., 2012; Gobillon & Wolff, 2016; Sogn-Grundvåg et al., 2021), livestock (Hobbs, 1997; Larue et al., 2016), cattle (Crespi & Sexton, 2004), wheat (Banerji & Meenakshi, 2004), timber (Roberts & Sweeting, 2013), and flowers (Steen, 2010).

Compared to negotiated sales, auctions have the advantage that buyers bid as rivals in a setting where all terms of exchange are specified except for price (Schrader & Henderson, 1980). This means that transactions can be carried out very fast, an important attribute for highly perishable commodities such as fresh fish (Brendstrup & Paarsch, 2006).[1] Additionally, with competing bidders, auctions are usually an efficient means of price discovery, and it has been shown that auctions lead to higher prices than negotiated sales (Bulow & Klemperer, 1996; Sogn-Grundvåg & Zhang, 2023a; Wolff & Asche, 2022).[2,3]

The efficiency of auctions is also indicated by a range of studies showing how prices of different lots of the same commodity can vary substantially due to variations in quality. For seafood auctions, the focus of this study, researchers have documented the impact on the price of quality attributes such as fish size (Kristofersson & Rickertsen, 2004; McConnell & Strand, 2000; Sogn-Grundvåg et al., 2019, 2020), fat content (Carroll et al., 2001; McConnell & Strand, 2000) and factors influencing quality such as fishing gear (Asche & Guillen, 2012; McConnell & Strand, 2000; Sogn-Grundvåg et al., 2020) and seasonality (Carroll et al., 2001; Sogn-Grundvåg et al., 2021) as well as auction design and strategic behavior (Guillotreau & Jiménez-Toribio, 2011; Vignes & Etienne, 2011).

It has also been shown that commodities of high quality have a higher probability for successful auction sales compared to lower-quality products (Sogn-Grundvåg & Zhang, 2023b). This is relevant because over-the-counter sales are often an option when an item goes unsold in an auction. In the auction for frozen cod in Norway, it was found that 2/3 of the lots that had previously gone unsold at the auction were later sold over the counter resulting in lower prices than auction sales (Sogn-Grundvåg & Zhang, 2023a).[4] In French timber auctions, the share of unsold lots can reach 50% (Préget & Waelbroeck, 2012), and in the UK, the share of live cattle sold through auctions declined from 80% in the 1950s to about 50% in the 1990s (Hobbs, 1997). When a high share of agricultural or seafood commodities go unsold and/or are sold directly, this may lead to reduced competition in the auction, lower prices, and affect auction efficiency negatively.

Thus, to utilize the benefits of auctions, attracting buyers is crucial to sellers and auction efficiency. In an English or open ascending price auction, the auctioneer typically opens the auction by announcing a suggested starting price set by the sellers.[5] A reserve price, that is, the seller's lowest acceptable price is also usually announced but may be kept secret to buyers in some auctions. Even with an auction design that maximize the efficiency of the auction, strategic behavior may be observed. For example, setting a low starting price may incentivize buyers to bid more than their initial valuations because early bids can act as sunk costs representing investments in terms of time and energy that cannot be recovered (Ku et al., 2005, 2006). Following the theory of "escalation of commitment" (Staw, 1976), bidders' inability to ignore sunk costs may lead them to go past their limits to try to justify their initial bid(s), leading them to bid more rather than withdraw, pushing prices higher as shown by Ku et al., (2005, 2006). This tendency for poor decision-making may be amplified by time pressure (Ku et al., 2005). This is particularly the case when some bidders place their bids at the last opportunity before the closing time, hoping to win the auction, a practice referred to as sniping in the literature (Ely & Hossain, 2009; Ku et al., 2005; Roth & Ockenfels, 2002). This strategic behavior is also important for the efficiency of the auctions as more bidders and bids may attract new bidders because increased auction activity provides more information about the true value of the auctioned item (Ku et al., 2006).

[1]In the auction for fresh pelagic fish in Norway, each auction last for 1 h (Sogn-Grundvåg et al., 2019).

[2]Buyer collusion can be difficult to discover and substantially reduce auction efficiency (Banerji & Meenakshi, 2004; Pesendorfer, 2000). Auction rules may also result in inefficient pricing, such as in the New Bedford seafood auction, where only buyers who have access to dock space can buy at the auction, and fish is auctioned by the boatload, meaning that quality-based pricing is not feasible (Peterson & Georgianna, 1988).

[3]Oglend et al. (2022) provide empirical evidence of the costs of price discovery in bilateral transactions.

[4]That over-the-counter prices are lower than auction prices is a common result, which at least can partly be explained by lower transaction prices (Wolff & Asche, 2022).

[5]The English auction is the oldest and perhaps the most prevalent auction mechanism (Krishna, 2003).

How sellers of agricultural and seafood commodities set start and reserve prices in auctions—and how this may affect key auction outcomes and efficiency—is a topic that has received little attention in the literature. A notable exception is a study by Zhang and Sogn-Grundvåg (2023) investigating the impact of reserve prices on bidder participation in the auction for frozen Atlantic cod in Norway. The study, which did not include starting prices, found no effect of reserve prices on bidder participation. This is perhaps not surprising given that sellers typically will set reserve prices reflecting actual market prices, and it seems unlikely that these are perceived as low by buyers. In contrast, the present study includes both start and reserve prices and utilizes the fact that some sellers set starting prices that are lower than reserve prices, and that the higher reserve prices can be used as a benchmark against which starting prices can be compared.

More specifically, we investigate the effect of low starting prices on key auction outcomes in the main auction for frozen saithe in Norway, organized as an ascending (English) auction with remote bidders. Here, start and reserve prices were the same in 45% of the auctioned lots ($n = 8217$) during the 6-year period studied (2017–2022). However, for all the remaining lots, starting prices were set lower than reserve prices. This variation in how sellers set starting prices in the auction allows us to examine three closely related hypotheses with significant implications for auction efficiency. These are that low starting prices would to a larger extent than high starting prices lead to: (1) a higher probability of successful auction sales, (2) increased competition, and (3) higher final prices.

The remainder of the article is organized as follows. In the next section, we describe the auction and data. Section 3 outlines the methodology, Section 4 presents the results, and Section 5 concludes the study.

2 | THE AUCTION AND DATA

The ex-vessel sale of wild-caught fish in Norway is legally regulated by the Raw Fish Act and is organized by sales organizations owned by fishers. The frozen saithe included in this study is sold through the Norwegian Fishermen's Sales Organization (NFSO),[6] which is responsible for the auction rules and is the auctioneer for frozen groundfish such as Atlantic cod, haddock, and saithe. The auction, which is open to all registered sellers and buyers and organized as an ascending English auction, is conducted online on the NFSO's auction website. On the auction website, all participants can see various details of each lot, such as the name of the vessel, the fishing gear used, the date and location of landing, the weight of the lot, the average size of the fish, and the start and reserve price.

After a discussion with the vessel owners to set start and reserve prices, the auctioneer publishes lots during normal working hours (8:00 a.m. to 4:00 p.m.). The closing time for each auction is between 10:00 a.m. and 00:30 p.m. the next day. The auctions for the different lots are closed with 3-min intervals, and the bidder with the highest bid at the closing time wins. According to the auctioneer, bidding activity increases when the closing time is approaching, and several buyers always place their bids when there are only seconds left, indicating time pressure for remaining buyers. However, if a bid is placed less than 20 s from the closing time, the auction is automatically extended with 20 s to allow time for competing bids.

Buyers place their bids manually or by an automatic bidding system. With manual bids, buyers push virtual buttons on the website with predefined price jumps of NOK 0.05, 0.10, 0.20, 0.50, or 1 per kilogram until the intended bid price is reached. With the automatic bidding system, bids are increased automatically with fixed incremental steps as competing bids are posted, up to a maximum price set by bidders. According to the auctioneer, it is not uncommon that bidders raise their maximum price if competing bids are higher than their initial upper limit, indicating

[6]Frozen saithe landed in the southern and western parts of Norway are sold through the Sunnmøre and Romsdal Fishermen's Sales Organization and Vest-Norges Fiskesalgslag.

"escalation of commitment" and overbidding. The size of price increments with automatic bidding is NOK 0.05, which can be considered a small price jump. This is important for auction efficiency because large, fixed bid increments in online bidding may prevent buyers from revealing their true valuation and lead to underbidding (Myrna, 2022).

As noted above, starting prices and reserve prices were the same in 45% of the transactions included in the data. Further examination shows that 21 out of 126 sellers consistently set the same starting and reserve prices. An interesting question is what motivates some sellers to set the same start and reserve prices? Anecdotal evidence based on discussions with sellers and buyers indicates different motivations. One seller argues that they set the same start and reserve prices because they want a high final price.[7] There are also claims that some sellers set the same start and reserve prices to avoid selling at the auction. They do so because they own trading businesses and want to sell their own fish to keep the trading business in operation and to gain an additional margin at the next level in the supply chain.

Immediately after an auction is finished, all information about winning bids, such as the name of the seller and buyer, the various characteristics of the lot, the date, and final prices, is available on the website to all participants (for 1 year after the transaction date). The high level of transparency means that when sellers set start and reserve prices for upcoming auctions, they have access to information about final prices for comparable lots in recent auctions.

The buyers are fish processors or trading companies reselling to fish processors mainly located in Europe and Asia, with China being a large market with processing for re-exports as the main activity (Asche et al., 2022). Buyers may value lots similarly because the final use of the commodity is similar, that is processing of ready-to-eat products. This indicates that the auction can be characterized as one with mainly common values (Armstrong, 2001; Sogn-Grundvåg & Zhang, 2023b). Thus, others' bids can be perceived as signals that an item has greater value than initially anticipated (Ku et al., 2005).

2.1 | Data and key variables

The data for this study consist of details of 8217 transactions covering 6 years (2017–2022). Among them, 5417 lots (66%) were sold at the auction. In total, 126 sellers and 59 buyers participated in these auctions, which included 101,570 tons of frozen-headed and gutted saithe. For fish lots sold at the auction, the volume was 704,235 tons at a sales value of NOK 1169 million. This corresponds to USD 133,712 million. The average annual real exchange rate between 2016 and 2022 was 8.746 NOK/USD (the ERS Agricultural Exchange Rate Data Set). The average number of bidders per auction was 2.22. In 30.6% of the auctions, there was only one bid, implying no competition.

For the lots sold at the auction, the average transaction price, starting price, and reserve price were NOK 15.38, 14.74 and 15.15 per kilogram, respectively. The average ratios of transaction prices to starting prices and to reserve prices were 1.051 and 1.021, with the respective standard deviations at 0.080 and 0.071.

To investigate whether starting prices affect key auction outcomes, we created a variable (*Spread*) based on the difference between reserve and starting prices, in NOK or percentage. This seems a reasonable approach because seller's reserve prices, which are set with access to information about final prices for comparable lots in recent auctions, are likely to be very close to the valuations of the buyer with the highest willingness to pay.[8] Thus, we consider reserve prices as a useful

[7]This may seem quite unproductive because it would likely lead to a high share of unsold lots, which is also the case for this seller. At the same time, the high start/reserve price is used as a starting point in subsequent over-the-counter sales, which may lead to high final prices (Galinsky et al., 2009). When two or more buyers are interested, this may involve multilateral bargaining further contributing to higher prices (Thomas & Wilson, 2002). At the same time, however, organizing such bargaining sessions implies additional transaction costs in the form of time and energy.

benchmark against which starting prices can be compared. Figure 1 shows an upward trend in the value of the spread in NOK.

The data include information of key quality attributes of each lot, such as the average size of the fish, the storage time, a quality indicator, and the fishing gear used, an important indicator of fish quality (Sogn-Grundvåg et al., 2020). The data also include the weight of each lot (in kilograms) and the daily transaction quantity. These attributes may affect how potential buyers perceive the value of each lot and affect auction participation and will thus be controlled for when investigating the impact of low versus high starting prices on key auction outcomes. Bid logs with the number of participating bidders in each auction are also included.

3 | ECONOMETRIC MODELS

We apply a binary logit model to estimate the impact of the spread between reserve and starting prices on the probability of auction sales (*Auction-Sold*, Model A) and the probability of two or more participating bidders in each auction (*Bidders-D*, Model B). Here, *Auction-Sold* is a dummy variable equaling one for lots sold in the auction and zero otherwise; for sold lots, the dummy variable *Bidders-D* equal one for deals with two or more bidders and zero for deals with one bidder only.

The logit model is represented by the following equations:

$$\Pr(Y_i = 1|\boldsymbol{X}, \text{Spread}) = \varphi(Z_i),$$

$Z_i = a_0 + a_1 \text{Spread}_i + \sum_{k=1}^{m} b_k X_{k,i} + \text{Fixed\_Effects} + U_i$, (Models A/B)

where Y_i is either *Auction-Sold* or *Bidders-D*; Pr (•) is a logistical distribution function, conditional on the spread and other control variables (the vector $\boldsymbol{X}$); U_i is an error term. Fixed effects control for seasonal variation and seller heterogeneity, including seasonal dummies and the dummies for the top vessels (sellers) in terms of sold quantity.

The natural exponent of a coefficient in Models A and B equals changes in the odds ratio in response to a one-unit change in the relevant variable. Following the common practice in the literature, we report the marginal effects of the covariates representing changes in the probability of lots being sold at the auction (or with two or more bidders) when a covariate of interest increases by one unit.

To investigate the effect of low starting prices on final prices, we use a hedonic price model with the following specification:

$\log(\text{Price}_i) = a_0 + a_1 \text{Spread}_i + \sum_{k=1}^{m} b_k X_{k,i} + \text{Fixed\_Effects} + U_i$. (Model C)

Using the spread (in NOK or %) in the models indicates a continuous relationship between the dependent variables (the probability of being sold at the auction, two or more bidders, and the final price) and the starting price relative to the reserve price. However, starting prices may affect these dependent variables in a stepwise way. Starting prices that equal reserve prices may affect the auction differently compared to those that are lower than reserve prices. To test the stepwise relationship between the spread between reserve and starting prices and *Unsold*, *Bidder-D*, or *Price*, we further set quantile dummies according to the value of the spread in NOK: *Spread-Q0* for *Spread* = 0 and *Spread-Q1–Q4* for *spreads* in the range (0, 0.25], (0.25, 0.5], (0.5, 1], and (1, 4], respectively.[9]

[8]Per a reviewer's suggestion, we estimated a standard hedonic price model (without Spread) and then compared the fitted values and final prices for fish lots with important attributes, namely trawl, A-quality, and lots in quantile 2 regarding transaction quantity, fish size, and storage time. The mean of the differences between the fitted values and final prices is −0.0014, indicating the appropriateness of using the final price as a proxy of the true value.

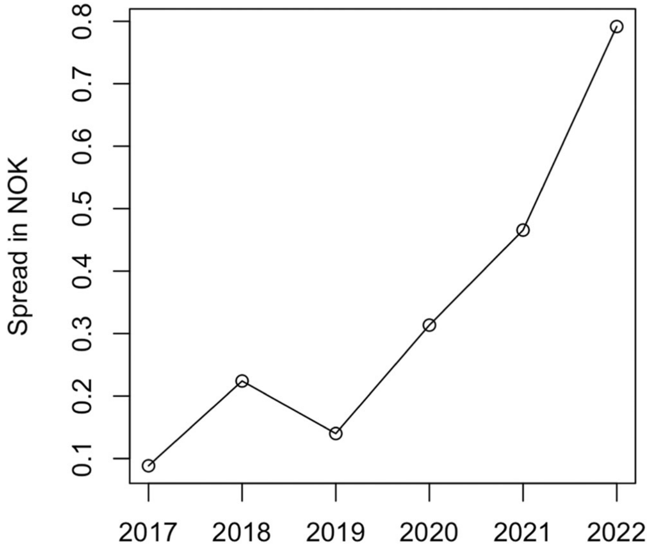

FIGURE 1 The average spread in NOK by year.

The control variables (***X***) include daily quantities, transaction quantities, fish size, storage time, a self-reported quality indicator, and fishing gear. Table 1 reports summary statistics for the variables in the three models. During the sample period, 67% of transactions were successfully sold at the auction, among which 69% had two or more bidders.

4 | EMPIRICAL RESULTS

Table 2 reports the estimation results for the models using *Spread* in NOK.[10] The coefficient of the spread is firmly significant in all three models. Taking the mean of the spread into account (Table 1), a 10% increase in the spread is equivalent to an increase of NOK 0.067 and 0.069 for the sample used for Model A and Models B and C, respectively. Thus, a 10% increase in the spread raises the probability of being sold at the auction by 1.70% (=0.067×0.2543) and the probability of two or more bidders by 1.79% (=0.069×0.2576). For Model C, a 10% increase in the spread lifts the final price by 0.43% (=0.069×0.0626). Among the control variables, *Transaction-Quantity*, *Storage-Time*, and *Quality-A* are significant in the three models, while *Fish-Size* is significant in Models B and C.[11]

Table 3 reports the estimation results for the models using *Spread* in percentage points. Again, the coefficient of *Spread* is firmly significant in the three models. A percentage point increase in the spread lead to an increase in the probability of being sold by 3.88%, the probability of two or more bidders by 3.64%, and the final price by 0.51%, respectively.

Table 4 reports estimation results using the quantile variables. In the three models, all quantile dummies are significant and positive. For each model, the coefficients of the quantile

[9]The limited unique values of the spread (see Supporting Information S1: Appendix S1) prevent us from setting the standard quantiles.

[10]For all regressions, we report robust and clustered (by sellers for Models A and B and sellers and buyers for Model C) standard errors. As a robustness check, we estimate all robust and clustered (by years) standard errors, which shows similar significant levels for *Spread* and other variables.

[11]There may be a nonlinear relationship between *Fish-Size* and final price. Thus, we added a quadratic term of *Fish-Size* in Model C. The estimation results (available upon request) show an insignificant coefficient of the quadratic term.

TABLE 1 Summary statistics.

Variable	Model A		Models B and C	
	Mean	SD	Mean	SD
Auction-Sold	0.67	0.47		
Bidders-D			0.69	0.46
Price, log			2.68	0.32
Spread in NOK	0.37	0.46	0.45	0.48
Spread in %	2.30	2.85	2.79	2.99
Spread-quantile 0	0.45	0.50	0	1
Spread-quantile 1	0.12	0.32	0	1
Spread-quantile 2	0.20	0.40	0	1
Spread-quantile 3	0.18	0.38	0	1
Spread-quantile 4	0.06	0.23	0	1
Quantity-Daily, log	11.59	1.46	3.04	13.95
Transaction-Quantity, log	7.50	2.31	2.40	12.50
Fish-Size, log	0.38	0.46	-0.22	2.08
Storage-Time, log	1.60	0.88	0	6.14
Trawl	0.83	0.37	0	1
Longline	0.05	0.21	0	1
Demersal-Seine	0.10	0.29	0	1
Quality-A	0.87	0.33	0	1
Quality-B	0.08	0.27	0	1
Original variable values				
Price, NOK/kg			15.38	4.78
Quantity-Daily, kg	201,417	188,389	199,269	179,029
Transaction-Quantity, kg	12,361	24,829	13,000	24,991
Fish-Size, kg	1.62	0.71	1.62	0.72
Storage-Time, days	8.21	16.66	7.54	17.55

dummies differ from each other. In general, the coefficient of *Spread-quantile* 1 is smaller than the coefficients of the higher-quantile dummies. For Model A, compared to lots with no differences between reserve and start prices, lots with a spread in the first quantile have a 14.5% greater probability of being sold at the auction; lots with a spread in the higher quantiles (*Spread-quantile* 2–4) have approximately 21% greater probability of being sold at the auction. Thus, there are significant differences in the impacts on successful auctions between *Spread-quantile* 0 and the higher quantiles. A similar pattern is found for the estimated coefficients of quantile dummies in Model B for *Bidders-D*, but *Spread-quantile* 4 has a marginally stronger impact on the probability of two or more bidders than *Spread-quantile* 2–3. For Model C, lots in *Spread-quantiles* 1 and 2 are sold at 3.99% and 6.8% higher final prices than lots in *Spread-*

TABLE 2 Estimation results for models using *Spread* in NOK.

Variable	Model A (Auction-Sold)	Model B (Bidders-D)	Model C (log(Price))
Spread in NOK	0.2543***	0.2576***	0.0626***
	[0.0325]	[0.0329]	[0.0092]
Quantity-Daily, log	0.001	0.0057	0.0018
	[0.0065]	[0.0082]	[0.0026]
Transaction-Quantity, log	0.0262***	0.0354***	0.0167***
	[0.0045]	[0.0036]	[0.0032]
Fish-Size, log	0.0034	0.0325**	0.1913***
	[0.0132]	[0.0171]	[0.0172]
Storage-Time, log	−0.0497***	−0.0403**	−0.0177***
	[0.0102]	[0.0159]	[0.0057]
Trawl	−0.1513***	0.017	0.0191
	[0.0446]	[0.0705]	[0.0231]
Longline	−0.0264	0.012	−0.0147
	[0.0682]	[0.0872]	[0.0271]
Demersal-Seine	−0.1103*	0.0754	−0.0228
	[0.0680]	[0.0660]	[0.0245]
Quality-A	−0.1685***	−0.0969**	0.3538***
	[0.0326]	[0.0458]	[0.0283]
Quality-B	0.0043	−0.0939	0.1131***
	[0.0698]	[0.0772]	[0.031]
Intercept			1.7498***
			[0.052]
Seller dummies	Yes	Yes	Yes
Buyer dummies			Yes
Time dummies	Yes	Yes	Yes
Pseudo R^2/adj. R^2	0.1388	0.1228	0.8243
Obs.	8217	5417	5417

Note: Robust and clustered standard errors are in brackets.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

quantile 0. The prices of lots in *Spread-quantiles* 3 and 4 are approximately 10% higher than prices of lots with no difference between reserve and starting prices.[12]

In the above results, Model B tests the impact of the price spread on *Bidders-D*, a dummy variable. We further estimate an ordinal logistic model for bidders equaling 1, 2, 3, and 4 or more

[12]We further test the monotonic (one-sided) pattern of the coefficients of quantile variables, showing the significant difference between *Spread-quantiles* 2 and 1 for all the models, between *Spread-quantiles* 3 and 2 for Model C, and between *Spread-quantiles* 4 and 3 for Models A and B.

TABLE 3 Estimation results for models using *Spread* in %.

Variable	Model A (Auction-Sold)	Model B (Bidders-D)	Model C (log(Price))
Spread in %	0.0388***	0.0364***	0.0051***
	[0.0052]	[0.0049]	[0.0012]
Quantity-Daily	-0.0001	0.0051	0.002
	[0.0065]	[0.0082]	[0.0027]
Transaction-Quantity	0.0262***	0.0360***	0.0173***
	[0.0045]	[0.0035]	[0.0033]
Fish-Size	0.0151	0.0466***	0.1931***
	[0.0134]	[0.0166]	[0.0172]
Storage-Time	−0.0513***	−0.0421***	−0.018***
	[0.0102]	[0.0159]	[0.0058]
Trawl	−0.1468***	0.0225	0.0203
	[0.0444]	[0.0716]	[0.0255]
Longline	−0.0311	0.0071	−0.0156
	[0.0679]	[0.0890]	[0.0292]
Demersal-Seine	−0.1073*	0.0757	−0.0197
	[0.0670]	[0.0662]	[0.0259]
Quality-A	−0.1578***	−0.0806	0.3587***
	[0.0369]	[0.0513]	[0.0291]
Quality-B	−0.013	−0.1092	0.1155***
	[0.0747]	[0.0828]	[0.0326]
Intercept			1.7371***
			[0.0532]
Seller dummies	Yes	Yes	Yes
Buyer dummies			Yes
Time dummies	Yes	Yes	Yes
Pseudo R^2/adj. R^2	0.1376	0.12	0.8208
Obs.	8217	5417	5417

Note: Robust and clustered standard errors are in brackets.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

bidders. The estimation results (available upon request) show that the spread significantly and positively affects the outcome, regardless of the measures. However, only the cut points between 2 and 3 bidders and between 3 and 4 or more bidders are significant at the 1% significant level.

Above all, although all quantile dummies have a positive impact on auction outcomes compared to the base (starting price = reserve price), there is a significant difference between quantile 1 and higher quantiles. In addition, the hedonic price model shows that the 3rd and 4th quantile dummies

TABLE 4 Estimation results using Spread-quantiles.

Variable	Model A (Auction-Sold)	Model B (Bidders-D)	Model C (Price)
Spread-quantile 1	0.1451***	0.1109***	0.0399***
	[0.0190]	[0.0243]	[0.0133]
Spread-quantile 2	0.2178***	0.2111***	0.068***
	[0.0150]	[0.0178]	[0.0107]
Spread-quantile 3	0.2105***	0.2170***	0.0981***
	[0.0187]	[0.0222]	[0.0102]
Spread-quantile 4	0.2163***	0.2501***	0.0991***
	[0.0221]	[0.0133]	[0.0077]
Quantity-Daily, log	−0.0023	0.0032	0.0006
	[0.0065]	[0.0080]	[0.0025]
Transaction-Quantity, log	0.0220***	0.0319***	0.0151***
	[0.0042]	[0.0032]	[0.003]
Fish-Size, log	−0.0053	0.0281*	0.1892***
	[0.0135]	[0.0170]	[0.0173]
Storage-Time, log	−0.0529***	−0.0441***	−0.0189***
	[0.0106]	[0.0164]	[0.0057]
Trawl	−0.1606***	0.0124	0.0207
	[0.0449]	[0.0795]	[0.0217]
Longline	−0.019	0.0255	−0.0134
	[0.0686]	[0.0928]	[0.0258]
Demersal-Seine	−0.1205*	0.0752	−0.0225
	[0.0714]	[0.0729]	[0.0235]
Quality-A	−0.1814***	−0.1125***	0.3525***
	[0.0312]	[0.0423]	[0.0276]
Quality-B	0.033	−0.0609	0.1176***
	[0.0664]	[0.0750]	[0.0303]
Intercept			1.7668***
			[0.0496]
Seller dummies	Yes	Yes	Yes
Buyer dummies			Yes
Time dummies	Yes	Yes	Yes
Pseudo R^2/adj. R^2	0.1484	0.1346	0.8279
Obs.	8217	5417	5417

Note: Robust and clustered standard errors are in brackets.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

have a stronger effect on the final prices than the 2nd and 1st quantile dummies. Taking the lowest bound of the 3rd quantile into account, we may suggest that the starting price should be about 0.5 NOK, or 3.3% lower than the reserve price.

5 | CONCLUSIONS

How sellers of food commodities set starting prices at auctions—and how this may affect important auction outcomes—is an aspect of strategic auction behavior that has not received much attention in the literature. This study analyses a detailed data set consisting of more than 8000 transactions between fishers and fish buyers in the largest Norwegian auction for frozen fish. The study finds support for the three suggested hypotheses: that a low starting price to a larger extent than a high starting price increases the probability of successful auction sales and a higher number of participating bidders, and it leads to higher final prices. These results clearly indicate that how sellers set starting prices can be important for both seller revenue and auction efficiency and represents a new contribution to the literature studying auction markets for food commodities.

The findings also have clear practical implications for sellers, auctioneers, and owners of auctions alike. Provided that reserve prices are set very close to prevailing market prices, starting prices should be set lower than reserve prices. To ensure a high share of successful auction sales, high competition, and high final prices, auction owners may consider a rule stating that starting prices should always be somewhat lower than reserve prices. Our results indicate that setting a starting price of about NOK 0.5, or 3.3% below the reserve price, would be sufficient to influence the key auction outcomes investigated here positively.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data is subject to third-party restrictions. Data used in this study are proprietary and cannot be shared.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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