HOUSING LAB WORKING PAPER SERIES

2025 | 3

Repeat bidder behavior in housing auctions

André K. Anundsen
Andreas Benedictow
Andreas E. Eriksen
Erling Røed Larsen
Mikkel Walbækken

HOUSING LAB
Nasjonalt senter for boligmarkedsforskning

Repeat bidder behavior in housing auctions*

André K. Anundsen[†], Andreas Benedictow[‡], Andreas E. Eriksen[§]
Erling Røed Larsen[¶], and Mikkel Walbækken[‖]

September 5, 2025

Abstract

Using data on more than one million bids from almost 200,000 housing transactions, we use a unique bidder identifier to follow bidders within and across auctions over the period 2007-2021. We retain information on bids for each repeat bidder during their participation in different housing auctions, in addition to unit-specific and auction-specific information. This data set allows us to estimate regression models with bidder-fixed effects to examine whether repeat bidders change their behavior as they participate in multiple auctions. We test the null hypothesis of no change in behavior along five parameters: unit size, ask price, nominal bid, bid relative to ask price, and bid relative to other bids. The evidence indicates that repeat bidders do not change the size or value of the units they seek to buy, but tend to change the way they bid.

Keywords: Auction data, bidding behavior, bid logs, housing market, repeat bidders
JEL Codes: D14; D44; D90; R21; R31

*We are grateful to DNB Eiendom for letting us analyze their auction data. We are grateful for comments from numerous participants in conference sessions and workshops, including AREUEA-ASSA Annual Meeting 2023, Western Economic Association International 2022, and the National Meeting of Norwegian Research Economists 2024. Thanks to Erlend Eide Bø, Teemu Lyytikäinen, and Oddbjørn Raaum for comments. An earlier version of this paper was part of Andreas E. Eriksen's PhD dissertation.

[†]Housing Lab, Oslo Metropolitan University.

[‡]Housing Lab, Oslo Metropolitan University and Samfunnsøkonomisk Analyse.

[§]School of Economics and Business, Norwegian University of Life Sciences and Housing Lab, Oslo Metropolitan University.

[¶]Housing Lab, Oslo Metropolitan University and Samfunnsøkonomisk Analyse.

[‖]Sopra Steria.

1 Introduction

Housing transactions are widely studied, but there is a paucity of knowledge on the behavior of bidders who experience that their bid fails and move on to bid for another house. We exploit detailed data on bidding logs and examine the behavior of bidders who participate in multiple housing auctions. In Norway, a typical house sale is arranged as a digital ascending-bid auction, in which bidders compete with other bidders in real-time as they submit bids while the real estate agent informs all participants of the development. Using our access to bid logs from one of the largest real estate firms in Norway, we follow bidders across auctions over time and study the size and value of the units for which they bid, the nominal level of the bids, the bids relative to the ask price, and the bids relative to competing bids. We aim to answer one question: Do repeat bidders change their mind or bidding behavior as they participate in multiple auctions?

We answer this question by distinguishing between targets and tools. Targets include the size and the value of the unit for which they are searching. Tools include the nominal bid level, the bid relative to the ask price, and the bid relative to competing bids. Our main findings are that repeat bidders tend to keep their targets unchanged across multiple auctions, but that they tend to change their bids relative to their own bids in their first auction, relative to the ask price, and relative to competing bids.

Our contribution is purely empirical. We bring five hypotheses to a novel data set that allows us to follow repeat bidders within and across auctions. Being able to follow repeat bidders implies that we can examine the dynamics of what units they seek to buy and how they go about bidding. It is reasonable to expect house buyers to make plans before entering the market. We expect these plans to be carefully made. After all, they have examined their needs and studied their budgets and attempted to find an optimal choice. Thus, it is of interest to economists and policy makers to find out how robust such planning is. However, households buy houses infrequently, so they do not have much knowledge about or experience from bidding dynamics. It would be a novel undertaking to assess to what extent they modify their behavior as they gain experience. Thus, we propose that the usefulness of our findings lies in what they say about consumer behavior in a market that is rarely visited but that involves a valuable asset. Our evidence is consistent with the idea that plans are relatively robust while bidding techniques are modified.

We define a repeat bidder as a buyer who is observed to place at least one bid in at least two auctions in our bidding log data. When we say ‘auction, this is short notation for ‘DNB auctions because our data are sourced from bidding logs from one real estate firm, DNB Eiendom AS; a company with a market share of about 20 percent. The data represent a new source of study, since the data set includes all bids, not only the winning bid, and the data set covers the period 2007–2021. We study these data to pose and test hypotheses of bidder behavior.

Our tests consists of regression analysis of five key behavioral dimensions. We use a battery of specifications. The specifications are tailor-made to the aim of finding out whether bidders change their targets (the size and price of units they seek to buy) or their tools (bids, in absolute and relative terms). In our most augmented regression model, we include bidder-fixed effects, year-fixed effects, and within-year calendar month fixed effects. We also include measures of market pressure, such as tightness and thickness. We partition the data set into one segment in which we have excluded the winning bid and one segment in which we have included the winning bid. Segmenting this way allows us to study both eventual-winners and non-winners as they participate in auctions and examine whether or not they change behavior as their experience base grows.

There are 16,454 bidders in our data set that are observed to have participated, by placing bids, in auctions of two or more units within a span of 270 days. We first study the size of the units for which they bid. Second, we study the ask price of the units. Third, we study the development across auctions of the nominal bids for the same repeat bidder. Fourth, we relate a given bidder's highest bid to the ask price of the unit, and study the development of this bid-ask ratio as bidders participate in more auctions. Fifth, we find the difference between the maximum and minimum range of bids for a given unit. Then, we compute the difference between a given bidder's highest bid and the lowest bid in that auction. Subsequently, we divide the latter by the former, and use the ratio as a metric to capture a bid's relative position within the auction bid range.

We cannot reject the null hypothesis that bidders tend to participate in auctions in which the size and ask price (value) of the unit are the same as the first auction. Our econometric setup cannot uncover causality, but detect associations. However, a careful interpretation of the results is that they are consistent with the idea that buyers do not appear to change their targets, that is, their plans. On the other hand, we reject the null hypothesis of no change with respect to nominal bid, bid in relation to ask price, and bid in relation to competing bids. This is consistent with the idea that bidders tend to change their tools, i.e., the way they go about bidding. We believe these findings help illuminate economic theory since the former is consistent with well-informed, forward-looking agents that use utility maximization given budget constraints to compute the size and price of the units they are looking for. The latter is consistent with learning. To be concrete, when bidders participate in auction number three they have more experience than when they participate in auction number one. In our examination of bids relative to competing bids we find that the coefficient estimates for the dummy variables 'Auction number 2' and 'Auction number 3' are, respectively, 0.012 and 0.03. The former is not statistically significant, but the latter is. The interpretation is that a bidder's participation in auction number three is associated with a fraction 0.03 of the range between the maximum and minimum bid in the auction.

The institutional set-up in Norway is favorable to studies of bidding behavior. Most importantly, a bid is legally binding and an acceptance of a bid is legally binding. The implication is that once a bid is accepted, the sale is essentially finalized. This structure and legal framework allow us to pinpoint the timing of winning bids down to the minute, which in turn makes it possible to construct accurate temporal breakdowns and to investigate sequences of bids. The auction format is also useful. In Norway, many house sales involve bids placed during a few hours, which makes it easy to control for the business cycle as bids are placed essentially at the same time and within the same macroeconomic environment. Although housing auctions in some countries may be associated with forced sales or foreclosures, the institutional arrangement of housing transactions in Norway is such that the default option is an ascending-bid auction. The typical auction starts with a listing on the online platform Finn.no. In that listing, a date for the open house is announced, and typically the listing is placed nine or ten days before the open house. The bidding starts the first work day after the open house. Today, bids are placed digitally using a national, digital identifier that relies on a registry of social security numbers. Earlier in the period, different technologies were used. Auctions differ in bidding frequency, bidding duration, increments of bids, and the use of bid expiration deadlines.

Related literature

Our findings relate to the literature on the distribution of bids (Levin and Pryce (2007)), the bargaining process in the housing market (Merlo and Ortalo-Magne (2004)), auction design (Milgrom and Weber (1982), Bikhchandani and Riley (1991), Arefeva and Meng (2020) and Ettinger and Michelucci (2019)), bidding strategies (Börgers and Dustman (2005), Dodonova (2017), Hungria-Gunnelin (2018) and Sønstebø et al. (2021)), jump bids (Avery (1998), Isaac et al. (2007), Ettinger and Michelucci (2016a), Ettinger and Michelucci (2016b) and Sommervoll (2020)) and anchoring effects (Anundsen et al. (2020) and Bucchianeri and Minson (2013).

This list of studies comprises only a few contributions into the growing literature on the transaction process, bidding behavior, and auction set-up in the housing market. Since the literature on this branch of housing economics is large, we cannot here do full justice to that literature. However, let us point to a few selected studies with themes into which we contribute. An early contribution was Horowitz (1986) who constructed a bidding model in which bidders make informed choices on which auction to enter and upper limits on the bid. Although the contribution was theoretical, he also used data from Baltimore from

1978. However, the focus of attention was on the estimation of the model while the aim of this paper is to follow bidders over time in order to investigate whether or not they change behavior. Since Horowitz (1986) many authors have examined bidding behavior, and for example Han and Strange (2014) study bidding wars in the housing market and show that they have become more frequent. This is a finding we are particularly interested in since the presence of bidding wars could lead participants to change behavior. We account for the effects of tightness and thickness. However, their focus of attention is on the historical frequencies of bidding wars while our aim is to inspect whether or not bidders change their bidding behavior as they gain more experience and participate in more auctions. Our finding that bids become more competitive as bidders participate in more auctions is one component that would contribute to bidding wars. Chow et al. (2015) compare auctions and negotiated sales and construct a model that has as one implication that the former tend to generate higher prices. By documenting that repeat bidders tend to change their bidding behavior in the direction of making more competitive bids, we offer empirical evidence that broadens the knowledge base of why auctions may function as a price driving set-up. This is also consistent with the findings in Arefeva (2017), who construct a search model that implies that auctions can generate higher price variance through competing bids. The dynamic created by the competition between multiple households over one unit, generates useful price signals because it shows what houses are attractive and which areas are in high demand. Genesove and Hansen (2023) show that auctions lead to prices that are useful in forecasts. We do not study the informational content generated by auctions, but we do study the mechanisms within them and the learning experience for bidders who have participated in them. So, when we inspect how repeat bidders change behavior as they participate in multiple auctions, we follow the mechanism that may lie behind the high information content in auction prices. Mateen et al. (2021) inspect 147,709 bargaining events in Redfin data to examine how information about buyers contributes to explain the resulting sell price by examining variables such as financing conditions, pre-inspection request and other terms.

They find that the estimated coefficients on effects are statistically significant. From another angle Arefeva and Meng (2020) seek to understand how sellers should set a deadline for bids when auctioning their houses, a problem which illustrates the richness of the interaction between bidders and sellers. Another example of this richness can be found in Smith (2020), who constructs a model that demonstrates that seller entry is dependent upon the number of buyers the sellers observe. Thus, this is an active area of research, but this paper's goal of exploring change in behavior among repeat bidders appears to warrant more examination.

The structure of the article is as follows. Section 2 describes the institutional arrangements of the Norwegian housing market, while Section 3 presents the data set on bidding logs and the repeat bidder data set. In Section 4, we explain our empirical techniques. In Section 5, we present our empirical results. In Section 6, we perform sensitivity and robustness checks. Section 7 concludes the paper.

2 Institutional background

The seller and buyer experience

The typical seller consults multiple real estate agents before choosing one, and the seller and the chosen agent discuss what ask price to list. They also set dates for the open house. During an auction, bids are placed with the real estate agent, and the agent advises the seller on what to do as bids arrive. If a bid is acceptable, the seller informs the real estate agent and this acceptance is legally binding.

Buyers decide on what type of housing unit they are looking for with respect to location, size, and price. Then, they browse online using Finn.no, which has a market share of at least 70 percent[1], searching for listings that fit their requirements and budgets. Buyers then attend open houses of promising units and, if they decide to attempt to buy, they volunteer their names on the list of interested parties. Buyers on this list will be informed by the real

[1]https://eiendomnorge.no/housing-price-statistics/category936.html

estate agent about developments in the auction. All placed bids are legally binding, but it is common practice to put expiration time and dates on a bid. The minute a bid is accepted, the transfer of ownership is legally irreversible.

Since most buyers are sellers, and *vice versa*, they have to make a decision on whether or not to buy before selling. In Norway, many people buy before they sell, knowing that the failed sales rate is low (see e.g., Anundsen et al. (2022)).

Regulation of real estate brokerage and auctions

The current law on real estate entails strict requirements for the real estate agent, but still allows for the sales process and auction to be set up differently by different real estate agents, companies, and parts of the country. The law sets no requirement that homes are sold on the basis of an auction, or a specific type of auction, presence of home-seller, or home-buyer insurance, etc. Yet, nearly all ordinary sales are arranged through an ascending-bid auction. Exceptions are inheritance settlements, divorce agreements, within-family transfers, etc. In recent years, regulation has been tightened. Since 2011, educational and practical requirements have been set for real estate agents and assistants, as well as for lawyers that undertake real estate agent assignments. As of 1 July 2010, the earliest possible acceptance deadline for a bid that is communicated via a real estate agent is at 12:00 PM the day after the last open house. Since 1 January 2014, real estate agents can only mediate (digitally) signed bids, acceptances, or rejections.

Auction arrangement and outcomes

The Real Estate Brokerage Act gives real estate agents room for maneuver in designing the sales process. Therefore, it is interesting to sellers, buyers, real estate agents, economists, and authorities how the construction of the auction architecture affects outcomes, especially the sell price, but also the bidding process, time-on-market (TOM), and other characteristics (number of bidders, number of bids per bidder, frequencies of short expiration bids, etc.).

Real estate agents are required to facilitate a fair and sound settlement of the auction and adjust the pace of the bidding so that both the seller and potential buyers have a basis for acting responsibly and in line with their own interests. However, current laws and regulations do not set clear requirements for the duration of the expiration deadlines. The exception is the requirement that the real estate agent cannot mediate bids with a deadline earlier than 12:00 PM the first working day after the last announced open-house.[2]

In Norway, the frequency of failed sales is low. Anundsen et al. (2022) report that Eiendomsverdi, a data analytics firm, counts sales not sold within 12 months of announcement. The rate varies by year, between three and six percent.

Conditional bids are allowed and conditions could include take-over date, interior or exterior decorative elements. Legally, conditions may include many aspects.

3 Data

The data set consists of Norwegian bidding log data provided by DNB Eiendom, which is the real estate agent arm of Norway's largest bank, DNB. DNB Eiendom (hereafter DNB) has a market share of 20 percent. Details about these data are provided in Appendix A. Our bidding log data set allows us to follow the same bidder across multiple auctions. Within the same auction, a bidder's maximum bid may be considerably larger than the bidder's minimum bid. A natural question is whether the maximum bid across auctions is relatively similar or quite different. In this article, we are particularly interested in studying patterns that involve a given bidder's maximum bid in each auction in which the bidder participates. To this end, we follow repeat auction participants, which we define as bidders that have participated in at least two auctions.

We define a repeat bidder as a bidder who participates in at least two auctions within a

[2]In Denmark and Sweden, home buyers in practice have more time. In Sweden, a bid is not binding, which constitutes an advantage for the highest bidder, who in the aftermath of the auction can assess the home with professional assistance and choose to withdraw the bid. In Denmark, it is possible to withdraw from the transaction against a fee that represents a percentage of the selling price.

span of 270 days. This means that they can be observed in at most two different calendar years. In Panel a of Figure 1 we show the distribution of how often we observe them – the observed experience. Most of the repeat bidder data consist of bidders observed in two auctions (88 percent), while a smaller minority are observed in three auctions (10 percent). In Panel b of Figure 1, we show a histogram of bids per bidder. More than 70 percent of the bidders place at least two bids and more than half place 3 or more bids in a given auction.

All steps taken to construct the repeat bidders data are provided in Table 1. Summary statistics of this data set are provided in Table 2. Notice that we include common debt in the computation in ask price since we shall use that feature in our analysis of repeat bidders.

Table 1: Construction of the repeat bidder data set

Cleaning step	# Auctions	# Bidders	# Bidder-Auction comb.
Initial	195,968	391,305	418,010
Drop secret and counter bids	195,837	390,990	417,655
Drop auctions with 1 bid	167,326	364,275	389,144
Keep bidders observed in at least 2 auctions	36,161	20,969	45,838
Drop missing time between first and last bid observed by bidder	35,982	20,848	45,523
Drop bidders observed over a longer period than 270 days	30,649	17,617	37,988
Keep bidders observed winning at most once	29,693	17,026	36,606
Drop bidders if observed after they win	28,877	16,480	35,379
Drop bidders if observed in more than 5 auctions	28,813	16,454	35,207

Notes: The table presents the steps taken from the bid-level data to the repeat bidders data. The column *Bidder-Auction comb.* presents the unique repeat bidder-auction combinations observed, that is, the total number of bidder-by-auction cases in the sample. To keep track of the sequence in which bidders are observed, we define the bidder participation in an auction as the last time the bidder placed a bid in that auction. That means, if the bidder placed a bid in an auction, then moved on to bidding on other units while the first auction did not end with a sale, and then came back bidding again at the first unit, the first unit will be the last in this sequence.

At the median, an auction has 3 bidders and 9 bids, and the median bidder places almost 3 bids in a given auction. The first bid in an auction is typically well below the ask price and at the mean it is almost 8 percent lower. The average spread between the opening bid and the winning bid is more than 9 percent. Auctions are speedy and at the median they are completed within 17 hours.

Table 2: Summary statistics for repeat bidder data. Norway, 2007–2021

	10^{th} pct.	25^{th} pct.	Median	Mean	75^{th} pct.	90^{th} pct.
Sale-specific						
These statistics include one-time bidders observed in auctions with repeat bidders						
No. bidders	2.00	2.00	3.00	3.42	4.00	6.00
No. bids	3.00	5.00	9.00	10.48	14.00	20.00
No. bids per bidder	1.50	2.00	2.67	3.08	3.67	5.00
First-bid-ask spr. (in %)	-17.67	-11.90	-6.98	-7.82	-2.70	0.00
Highest-lowest bid spr. (in %)	2.14	3.95	7.22	9.38	12.28	18.92
Auction duration (in hours)	1.70	3.07	16.97	238.70	72.54	480.46
Sell-Ask spr. (in %)	-3.23	0.00	5.00	6.72	11.93	19.09
Ask (in million NOK)	1.60	2.04	2.64	2.85	3.40	4.34
Size (in sqm.)	43.00	56.00	74.00	88.74	113.00	155.00
Bidder-specific						
Avg. highest bid/ask	0.93	0.97	1.02	1.02	1.06	1.11
Avg. relative bid position	0.33	0.50	0.71	0.67	0.88	0.96
Weeks from first observed	0.00	1.00	3.00	6.23	8.65	18.00
General						
Owner-occupied (in %)				62.60		
Oslo (in %)				29.04		
Winners (in %)				44.72		
No. repeat bidders				16,454		
No. bids by repeat bidders				101,280		
No. sales involving repeat bidders				28,813		
No. bidder-auction comb.				35,207		

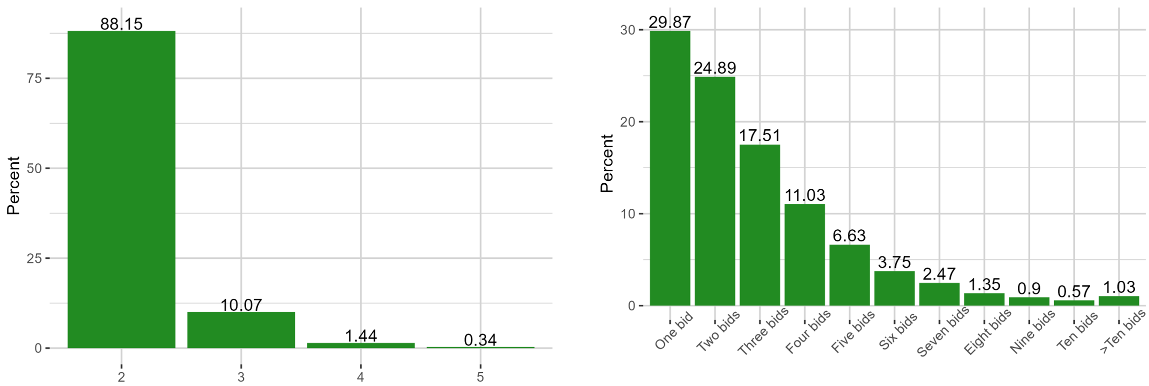
Notes: We define repeat bidder data as a data set that covers observations that involve bidders that are observed to participate in at least two auctions, such that each row represents one bidder's participation in one auction. Since one auction may contain two repeat bidders, there is a difference between the number of auctions (28,813) in the repeat data set and the number of unique repeat bidder-auction combinations (35,207). This implies that a repeat bidder that participates in n auctions is represented by n rows. The table shows summary statistics for repeat bidder data over the period 2007 – 2021. We have calculated the mean and median, in addition to the 10^{th}, 25^{th}, 75^{th}, and 90^{th} percentiles for each variable. All calculations are based on auction-logs from the real estate agent-firm DNB Eiendom. We include common debt in the computation of ask price. Statistics for *Weeks since first observed* leaves out the first time observed, which by construction takes the value zero.

4 Empirical techniques

4.1 Model specification

Our main contribution is the regression results from testing hypotheses on how bidders behave when they participate in more than one auction.[3] Do bidders change behavior in

[3]When we write auctions, this is short notation for DNB auctions since we do not observe auctions in other real estate companies.



(a) Bidders per observed experience group

(b) Bids per bidder

Figure 1: Panel a) shows the distribution of the number of bidders per observed experience group in the repeat bidders data. Panel b) shows the distribution of the number of bids placed by a given bidder in the repeat bidders data. Calculations are based on auction-logs from the real estate agent-firm DNB Eiendom.

terms of what units they seek to buy, how their bids compare to ask price, and how their bids compare to competitors? It is an empirical question whether bidders change behavior as they participate in more auctions since both a finding of no change in behavior and a finding of changed behavior can be explained by theory. No change in behavior would be consistent with a theory of forward-looking behavior of fully informed individuals who have acquired the required knowledge base before the first auction. A change in behavior would be consistent with a theory in which learning is a key component.

This article proposes that bidders think in terms of targets and tools. They target a housing unit's size and price (we take location as a given). They use nominal and relative bids as tools to that end. Thus, we study five variables: size, ask price, nominal bid, bid relative to ask price, and bid relative to competing bids.

Our null hypotheses are that bidders, across auctions:

1. Bid on equally sized units

2. Bid on equally priced units

3. Place maximum bids that are of equal nominal values

4. Place maximum bids that have equal bid-ask spreads
5. Place maximum bids that have equal relative distance to the maximum bid in the auction

We test our hypotheses by estimating regression models on two segments of data. In our first segment, we remove the observation that contains the winning bid. Our second segment includes the observation that contains the winning bid. Our thinking is that there might be an endogeneity issue in the winning bid since the decision to extend a nominal bid and it being of the nature that it wins are rooted in the decision process of the winning bidder. However, we keep our second segment because we find it interesting to examine the qualities of winners' winning bid.

For the first segment, we estimate three regression models, and the augmented specification takes the following form:

$$\begin{aligned} Z_{b,y,m,ba} =& FE_b + FE_y + FE_m + \beta_2 AuN2_{ba} + ...\beta_5 AuN5_{ba} \\ & + \beta_6 TIGHT_{ba} + \beta_7 THICK_{ba} + \varepsilon_{ba}, \end{aligned} \tag{1}$$

in which FE_b, FE_y, and FE_m are bidder, year, and intra-year monthly fixed effects and subscript ba represents a running number of bidder-auction combinations. For example, if bidder $b = A$ participates in three auctions ($a = x, y, z$) and bidder $b = B$ participates in four auctions ($a = x, y, w, r$), there would be seven unique bidder-auction combinations, two unique repeat bidders, and four unique auctions. Then, these bidder-auction combinations ba would represent seven observations. The variables $AuN2_{ba}$, ..., $AuN5_{ba}$ are four dummy variables in which each dummy variable is unity for the bidder-auction combination in which bidder b is observed to participate, and where $i = 2, 3, 4, 5$ is the observed sequence in which the bidder is observed. $i = 1$ is the default, so that coefficient estimates are interpreted relative to the first time repeat bidders are observed bidding.

The variables $TIGHT_{ba}$ and $THICK_{ba}$ are control variables that let us account for the market situation at the date when the bidder is observed. For instance, we expect that repeat bidders will be less prone to change behavior during periods of low tightness due to low competition between bidders. The market situation is measured by market tightness and thickness, which are both calculated using inferred numbers of active buyers and sellers in the market. Tightness is calculated by dividing the number of active buyers by the number of active sellers and thickness takes the sum of the number of active buyers and sellers.

For the second segment, we estimate four regression models, in which three of them have the same specification as above. The last regression model includes an interaction variable between the four auction number dummy variables and a dummy 'Winner' which is unity for a repeat bidder that is observed to win an auction.

In our regression models, we use five dependent variables Z and for each of these five variables, we estimate seven regression models for the two above-mentioned data segments.

The five dependent variables Z are:

1. Size of the unit in auction a for which a given bidder b bids
2. The ask price of the unit in auction a for which a given bidder b bids
3. The highest bid a bidder b places in an auction a
4. The bid a given bidder b places compared to the ask price in auction a
5. The highest bid bidder b places less the minimum bid in auction a divided by the difference between the maximum and the minimum bids in the auction, $(bid_{ba} - min_a)/(max_a - min_a)$

We use as a maintained assumption that a bidder visits units that are sold by different real estate agents randomly. DNB has a market share of 20 percent, thus we observe only one out of five auctions in which a bidder participates.[4] A given bidder that is observed to participate in two auctions in our data set may have participated in other non-observed

[4]Anundsen et al. (2022) perform a check for balance between the DNB sample and a larger housing transaction sample comprising most transactions listed on the online platform Finn.no. They conclude that the DNB sample is representative for the market.

auctions. We assume that the participation sequencing is random between real estate agents. The implication is that for a bidder A that in total participates in ten auctions, out of which two are registered in DNB data, the sequence number of those two can be modeled as two numbers drawn randomly without replacement from ten numbers, 1 through 10. This implies that the coefficient estimates will represent the average change in behavior across the sequence of auctions the further out in the sequence bidders are.

Moreover, the sequence we observe is the lower bound of the true sequence. Assume that bidder B participates in ten auctions but is observed in four auctions in the DNB data. We do not know much about the relation between these four observable auctions and the true ten auctions, six of which are unobserved to us. If three of our observations are temporally close and one is temporally distant, it could be argued that it is likely that B participates in other auctions in between. Provided that the relationship is monotonic, there are four possibilities for how this may affect estimates. First, if the true effect of number four is the same as number ten, then the estimates are not biased. Second, if the true effect of number four is weaker than number ten, then the estimates may be biased upwards because true number four and upwards will be categorized as number four in the data. Third, if the true effect of number four is stronger than number ten, then the estimates may be biased downwards. Fourth, if there are mixed types, meaning that certain bidder types increasingly adjust their behavior while other types reduce the extent of their adjustment when losing auctions, then both the presence and the direction of the bias depend on which types are more prevalent in the data. However, bidder type should be accounted for by bidder FE, which alleviates some of the concern about biased estimates. Moreover, in order to reject the null, it is sufficient that changes in behavior is monotonically increasing or decreasing. Thus, for our purpose of investigating whether or not bidders change behavior, unobserved auction participation is not a worry as long as the effect, i.e., the sign of the coefficient, of participating in auctions is the same across auctions.

4.2 Five hypotheses

We test the following five null hypotheses on repeat bidder behavior across multiple auctions:

1. No change in the size of the unit in auction a for which a given bidder b bids
2. No change in the ask price of the unit in auction a for which a given bidder b bids
3. No change in the highest bid a bidder b places in an auction a
4. No change in the bid a given bidder b places compared to the ask price in auction a
5. No change in the highest bid bidder b places less the minimum bid in auction a divided by the difference between the maximum and minimum bids in the auction, $(bid_{ba} - min_a)/(max_a - min_a)$

5 Empirical results

5.1 Key findings

We cannot reject the first two hypotheses, but we do reject the last three hypotheses. The implication is that we find that repeat bidders display behavior, when they participate in more auctions, that is associated with no change in the size of the unit they seek and value of the unit. Repeat bidders tend, however, to display behavior that is observed to imply increases in their nominal bids, their bids relative to the ask price, and their bids relative to competing bids.

5.2 Size

Table 3 tabulates our results when we regress unit size onto the specified determinants in equation (1). Our preferred model is Model 3 since this specification includes bidder, year, and intra-year month fixed effects, a tightness measure, and a thickness measure. In addition, the regression model is estimated on a data segment that does not include the winning bid, which dampens the danger for potential endogeneity issues. We observe that three out of four coefficient estimates for the dummy variables connected to auction number are negative, a finding that indicates a tendency among repeat bidders to seek out units that are smaller. However, the coefficient estimates are not statistically significant. Thus, we cannot reject the null of no change. The estimated coefficients are small, and the estimate of Auction number 2 in Model 3 is - 0.3. The interpretation of the magnitude of the coefficient is that when bidders have lost an auction, in the next auction they are observed to seek out a unit that is 0.3 square meters smaller, a negligible size change. The estimate is neither statistically significant nor economically meaningful.

Regression models 4 through 7 are estimated on a data sample that includes winning bids. We observe that this inclusion does not appear to change the coefficient estimates of the four 'Auction number'-dummies much. The augmented Model 7 yields a coefficient estimate of 'Auction number = 2' of -0.261, which is very similar to the estimate of -0.3 in Model 3.

Table 3: Unit size. Regressions of unit size on auction number

	Drop last auction of winner			Keep last auction of winner			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Auction number = 2	-0.009	-0.030	-0.300	-0.203	-0.231	-0.531*	-0.261
	(0.396)	(0.367)	(0.383)	(0.284)	(0.293)	(0.252)	(0.320)
Auction number = 3	0.194	0.165	-0.316	-0.462	-0.506	-1.007	-0.080
	(0.739)	(0.662)	(0.747)	(0.545)	(0.520)	(0.725)	(0.873)
Auction number = 4	0.645	0.586	0.063	0.572	0.491	-0.196	-0.303
	(1.536)	(1.573)	(1.598)	(1.438)	(1.455)	(1.436)	(1.489)
Auction number = 5	-0.429	-0.463	-0.712	1.243	1.196	0.584	-0.836
	(1.634)	(1.539)	(2.303)	(1.789)	(1.821)	(2.548)	(2.288)
Tightness		0.102	-0.189		0.189	0.107	0.112
(daily buyers/sellers)		(0.273)	(0.434)		(0.240)	(0.298)	(0.296)
Thickness		0.065	-0.392		0.071	-0.458	-0.473
(daily buyers+sellers)		(0.557)	(0.927)		(0.550)	(0.848)	(0.850)
Auction number = 2							-0.593
× Winner							(0.477)
Auction number = 3							-2.238
× Winner							(1.719)
Auction number = 4							0.350
× Winner							(2.087)
Auction number = 5							4.842
× Winner							(6.321)
Observations	17,501	17,501	17,501	28,853	28,849	28,849	28,849
Adjusted R^2	0.847	0.847	0.848	0.846	0.846	0.846	0.846
Bidder FE	✓	✓	✓	✓	✓	✓	✓
Intra-year calendar FE			✓			✓	✓
Year FE			✓			✓	✓

Notes: The table shows results of regressing the size in square meters on the bidder-auction combination *ba* on the auction number. We choose to drop bidders if they are observed to bid on different unit types, e.g., first a detached house and then an apartment. If bidders are observed to win but still place bids afterwards, they are dropped from the sample. *Tightness* (*Thickness*) is the number of buyers divided by (added with) the number of sellers on the market. Non-repeat bidders are assumed to be active on the market within 270 days after they are observed placing bids and not winning, and repeat bidders are assumed active on the market between the first and last time they are observed. *Winner* is a dummy variable indicating whether the bidder is observed winning the final auction she participates in. This dummy is included as a helping variable but is not reported because of the bidder fixed-effects. *Bidder FE* are bidder fixed-effects, *Intra-year calendar FE* are seasonal monthly fixed effects, and *Year FE* are year fixed-effects. We retain bidders that have participated in five or less auctions. Standard errors are two-way clustered on two-digit zip codes and year, and are given in parenthesis. Significance: * p<0.1, ** p<0.05, *** p<0.01.

5.3 Ask price

Table 4 tabulates our results when we regress ask price (in NOK 1,000) onto the specified determinants in equation (1). Again, our preferred model is Model 3 since this specification includes bidder, year, and intra-year month fixed effects, a tightness measure, and a thickness measure. We observe that three out of four coefficient estimates for auction number are positive, but that the coefficient estimates are not statistically significant. Thus, we cannot reject the null of no change. The estimated coefficients are also small, and the estimate in Model 3 of 'Auction number = 2' is 12,1. This estimate implies that, all else being equal, a repeat bidder in the second auction is observed to bid for a unit that has an ask price that is NOK 12,100 higher than the unit in the first auction. At at USD/NOK-rate of around 10[5], this translates into USD 1,200. For a typical unit at an average ask price of NOK 2.64 million (Table 2), NOK 12 000 amounts to half of one percent.

The coefficient estimates for 'Auction number = 2' across our seven specifications, vary in magnitude and statistical significance. However, the four models that yield statistically significant coefficient estimates do not control year and intra-year fixed effects, which means that if there is a price trend, a repeat bidder faces higher prices as time goes on. Thus, for the nominal variable 'ask price', controlling for time fixed effects is key. The coefficient estimates across the four dummies of 'Auction number' vary in magnitude. For Model 3, they range from -32.6 to 19.6. Economically, these numbers are small, from -1.4 percent to 0.8 percent. Thus, we cannot reject the null hypothesis that a repeat bidder searches for units, across auctions, that have the same ask price as the ask price of the first unit, for which he or she bid.

5.4 Bid

Table 5 tabulates our results when we regress bids (in NOK 1,000) onto the specified determinants in equation (1). We observe for our preferred Model 3 that all four coefficient estimates

[5] On June 13, 2025 the exchange rate is NOK 9.95 per dollar.

Table 4: Ask price (in NOK 1,000). Regression of the unit ask price on auction number

	Drop last auction of winner			Keep last auction of winner			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Auction number = 2	40.8***	40.8***	12.1	21.4***	21.2***	-9.65	8.45
	(7.10)	(6.99)	(9.42)	(5.70)	(5.89)	(5.80)	(6.66)
Auction number = 3	67.6***	67.7***	19.6	45.3***	44.8***	-5.97	21.1
	(15.6)	(16.1)	(17.1)	(10.8)	(10.5)	(12.1)	(17.4)
Auction number = 4	77.9***	77.2***	15.5	67.0***	66.4**	0.655	9.94
	(21.0)	(22.6)	(29.0)	(20.8)	(22.4)	(19.6)	(27.5)
Auction number = 5	49.0*	50.5*	-32.6	47.5	48.5	-35.4	-34.8
	(24.5)	(24.1)	(42.2)	(53.1)	(52.8)	(60.0)	(38.7)
Tightness		7.20*	4.81		9.12**	10.5*	10.6*
(daily buyers/sellers)		(3.74)	(5.47)		(4.23)	(5.19)	(5.10)
Thickness		-7.08	-5.56		-7.75	-7.66	-8.38
(daily buyers+sellers)		(10.0)	(11.0)		(9.15)	(10.3)	(10.1)
Auction number = 2							-39.7***
× Winner							(9.15)
Auction number = 3							-61.7**
× Winner							(26.1)
Auction number = 4							-18.2
× Winner							(41.1)
Auction number = 5							10.2
× Winner							(177.0)
Observations	21,313	21,311	21,311	35,207	35,201	35,201	35,201
Adjusted R^2	0.880	0.880	0.880	0.883	0.883	0.884	0.884
Bidder FE	✓	✓	✓	✓	✓	✓	✓
Intra-year calendar FE			✓			✓	✓
Year FE			✓			✓	✓

Notes: The table shows results of regressing the nominal ask price (measured NOK 1,000) on the auction number for the bidder-auction combination *ba*. If bidders are observed to win but still place bids afterwards, they are dropped from the sample. *Tightness* (*Thickness*) is the number of buyers divided by (added with) the number of sellers on the market. Non-repeat bidders are assumed to be active on the market within 270 days after they are observed placing bids and not winning, and repeat bidders are assumed active on the market between the first and last time they are observed. *Winner* is a dummy variable indicating whether the bidder is observed winning the final auction she participates in. This dummy is included as a helping variable but is not reported because of the bidder fixed-effects. *Bidder FE* are bidder fixed-effects, *Intra-year calendar FE* are seasonal monthly fixed effects, and *Year FE* are year fixed-effects. We retain bidders that have participated in five or less auctions. Standard errors are two-way clustered on two-digit zip codes and year, and are given in parenthesis. Significance: * p<0.1, ** p<0.05, *** p<0.01.

for auction number are positive, statistically significant, and economically meaningful. Thus, we reject the null of no change.

For 'Auction number = 2' the estimated coefficient is 31.1. The interpretation is that a repeat bidder in the second observed auction is associated with a bid that is NOK 31,100 higher than in the first auction, in which she or he lost. For a typical unit at an average ask price of NOK 2.64 million (Table 2), NOK 31,100 amounts to 1.2 percent, thus it represents a meaningful amount of money. The estimated coefficients increase in auction number, and the estimates are, respectively, 31.1, 54.0, 68.8, and 75.6. Thus, a repeat bidder's participation in auction number 5 is associated with a bid that is NOK 75,600 higher than the bid in the first auction. For average units, such a bid represents an increase of 2.9 percent.

While we found that bidders sought same-size and same-value units (targets) across auctions, we reject the null hypothesis of no change with respect to bids.

5.5 Bid relative to ask price

Table 6 tabulates our results when we regress bids relative to ask price onto the specified determinants in equation (1). We observe for our preferred Model 3 that all four coefficient auction number estimates are positive, statistically significant, and economically meaningful. Thus, we reject the null of no change.

The estimated coefficient for 'Auction number = 2' is 0.007. The interpretation is that a bidder's bid is 0.7 percent higher compared to ask price when the bidder is observed to participate in her or his second auction. In the fifth auction, the bid tends to be 3.1 percent higher. We also observe that the estimated coefficients are relatively stable across specifications and sample. There are seven models and five auction number coefficients in each model. All 35 estimated coefficients are positive and only one is not statistically significant.

5.6 Relative position of bid

Table 7 tabulates our results when we regress bids relative to other bids onto the specified determinants in equation (1). We observe that for our preferred Model 3 all four auction number coefficient estimates are positive and economically meaningful. We find that three

Table 5: Bid (in NOK 1,000). Regression of bidders' highest bids within auctions on auction number

	Drop last auction of winner			Keep last auction of winner			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Auction number = 2	64.1***	63.4***	31.1***	50.2***	49.6***	14.0*	25.5***
	(7.13)	(7.39)	(8.58)	(6.33)	(6.64)	(6.86)	(6.83)
Auction number = 3	108.9***	107.8***	54.0***	96.8***	95.7***	37.0***	49.9***
	(15.9)	(16.8)	(16.4)	(10.7)	(10.8)	(11.5)	(16.5)
Auction number = 4	139.5***	137.9***	68.8**	147.4***	145.9***	69.9**	50.1
	(24.3)	(25.6)	(28.1)	(28.1)	(30.1)	(24.5)	(36.4)
Auction number = 5	170.8***	169.4***	75.6	149.0**	148.3**	50.3	65.3
	(35.2)	(38.8)	(51.0)	(57.4)	(59.1)	(60.9)	(45.5)
Tightness		0.366	3.20		4.09	10.7	10.9
(daily buyers/sellers)		(5.22)	(5.91)		(5.37)	(6.34)	(6.25)
Thickness		5.55	12.2		1.14	6.98	6.46
(daily buyers+sellers)		(10.3)	(8.47)		(8.30)	(11.5)	(11.2)
Auction number = 2							-25.1*
× Winner							(13.1)
Auction number = 3							-28.9
× Winner							(31.3)
Auction number = 4							52.6
× Winner							(55.2)
Auction number = 5							-40.2
× Winner							(138.1)
Observations	21,313	21,311	21,311	35,207	35,201	35,201	35,201
Adjusted R^2	0.881	0.881	0.882	0.888	0.888	0.889	0.889
Bidder FE	✓	✓	✓	✓	✓	✓	✓
Intra-year calendar FE			✓			✓	✓
Year FE			✓			✓	✓

Notes: The table shows results of regressing bidders' highest nominal bids within auctions (measured in NOK 1,000) on the auction number for the bidder-auction combination *ba*. If bidders are observed to win but still place bids afterwards, they are dropped from the sample. *Tightness* (*Thickness*) is the number of buyers divided by (added with) the number of sellers on the market. Non-repeat bidders are assumed to be active on the market within 270 days after they are observed placing bids and not winning, and repeat bidders are assumed active on the market between the first and last time they are observed. *Winner* is a dummy variable indicating whether the bidder is observed winning the final auction she participates in. This dummy is included as a helping variable but is not reported because of the bidder fixed-effects. *Bidder FE* are bidder fixed-effects, *Intra-year calendar FE* are seasonal monthly fixed effects, and *Year FE* are year fixed-effects. We retain bidders that have participated in five or less auctions. Standard errors are two-way clustered on two-digit zip codes and year, and are given in parenthesis. Significance: * p<0.1, ** p<0.05, *** p<0.01.

out of four estimated coefficients are statistically significant. Thus, we reject the null of no change.

The estimated coefficient for 'Auction number = 3' is 0.03. The interpretation is that a

Table 6: Bids relative to ask price. Regressions of the bid-ask price ratio on auction number

	Drop last auction of winner			Keep last auction of winner			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Auction number = 2	0.008***	0.008***	0.007***	0.011***	0.010***	0.009***	0.006***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Auction number = 3	0.015***	0.014***	0.012***	0.020***	0.020***	0.017***	0.010***
	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
Auction number = 4	0.020***	0.020***	0.017***	0.029***	0.028***	0.025***	0.013
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.008)
Auction number = 5	0.036***	0.035***	0.031***	0.034**	0.033**	0.028**	0.028***
	(0.007)	(0.007)	(0.005)	(0.012)	(0.012)	(0.012)	(0.006)
Tightness		-0.002**	0.000		-0.002*	0.000	0.000
(daily buyers/sellers)		(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Thickness		0.005***	0.007**		0.004**	0.006**	0.006**
(daily buyers+sellers)		(0.002)	(0.003)		(0.002)	(0.002)	(0.003)
Auction number = 2							0.006
× Winner							(0.004)
Auction number = 3							0.015**
× Winner							(0.007)
Auction number = 4							0.029**
× Winner							(0.013)
Auction number = 5							-0.004
× Winner							(0.017)
Observations	21,313	21,311	21,311	35,207	35,201	35,201	35,201
Adjusted R^2	0.273	0.274	0.274	0.275	0.276	0.277	0.278
Bidder FE	✓	✓	✓	✓	✓	✓	✓
Intra-year calendar FE			✓			✓	✓
Year FE			✓			✓	✓

Notes: The table shows results of regressing bidders' highest bids within auctions relative to the ask price on the auction number for the bidder-auction combination *ba*. If bidders are observed to win but still place bids afterwards, they are dropped from the sample. *Tightness* (*Thickness*) is the number of buyers divided by (added with) the number of sellers on the market. Non-repeat bidders are assumed to be active on the market within 270 days after they are observed placing bids and not winning, and repeat bidders are assumed active on the market between the first and last time they are observed. *Winner* is a dummy variable indicating whether the bidder is observed winning the final auction she participates in. This dummy is included as a helping variable but is not reported because of the bidder fixed-effects. *Bidder FE* are bidder fixed-effects, *Intra-year calendar FE* are seasonal monthly fixed effects, and *Year FE* are year fixed-effects. We retain bidders that have participated in five or less auctions. Standard errors are two-way clustered on two-digit zip codes and year, and are given in parenthesis. Significance: * p<0.1, ** p<0.05, *** p<0.01.

bidder's bid in auction number three is associated with a bid that is a fraction 0.03 of the range between the maximum and minimum bid in the auction. In the fifth auction, the bid is a fraction 0.096 higher of the range.

Table 7: Relative bid position of repeat bidders. Regressions of the bid's position along the max-min range on auction number

	Drop last auction of winner			Keep last auction of winner			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Auction number = 2	0.021***	0.020***	0.012	0.156***	0.155***	0.148***	0.009
	(0.005)	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Auction number = 3	0.044***	0.042***	0.030**	0.245***	0.244***	0.232***	0.025
	(0.013)	(0.013)	(0.012)	(0.017)	(0.018)	(0.016)	(0.015)
Auction number = 4	0.083***	0.081***	0.066**	0.306***	0.305***	0.291***	0.047
	(0.021)	(0.020)	(0.024)	(0.035)	(0.035)	(0.036)	(0.030)
Auction number = 5	0.113*	0.111*	0.096*	0.352***	0.350***	0.337***	0.090
	(0.059)	(0.059)	(0.049)	(0.045)	(0.046)	(0.040)	(0.053)
Tightness		-0.003	-0.001		0.000	0.000	-0.001
(daily buyers/sellers)		(0.003)	(0.004)		(0.003)	(0.003)	(0.005)
Thickness		0.010	0.000		0.005	-0.005***	0.000
(daily buyers+sellers)		(0.007)	(0.007)		(0.004)	(0.002)	(0.003)
Auction number = 2							0.308***
× Winner							(0.012)
Auction number = 3							0.477***
× Winner							(0.023)
Auction number = 4							0.579***
× Winner							(0.037)
Auction number = 5							0.632***
× Winner							(0.093)
Observations	21,278	21,276	21,276	34,912	34,906	34,906	34,906
Adjusted R^2	0.096	0.097	0.097	0.162	0.162	0.163	0.266
Bidder FE	✓	✓	✓	✓	✓	✓	✓
Intra-year calendar FE			✓			✓	✓
Year FE			✓			✓	✓

Notes: The table shows results of regressing the relative bid position on the auction number for the bidder-auction combination ba. If bidders are observed to win but still place bids afterwards, they are dropped from the sample. The relative bid position is defined as the ratio between a given bidder b's highest bid in auction a less the global minimum bid in auction a on the difference between the global maximum bid in auction a and the global minimum bid in auction a, (Highest $\text{bid}_{b,a}$ − Minimum bid_a)/ (Maximum bid_a − Minimum bid_a). *Tightness* (*Thickness*) is the number of buyers divided by (added with) the number of sellers on the market. Non-repeat bidders are assumed to be active on the market within 270 days after they are observed placing bids and not winning, and repeat bidders are assumed active on the market between the first and last time they are observed. *Winner* is a dummy variable indicating whether the bidder is observed winning the final auction she participates in. This dummy is included as a helping variable but is not reported because of the bidder fixed-effects. *Bidder FE* are bidder fixed-effects, *Intra-year calendar FE* are seasonal monthly fixed effects, and *Year FE* are year fixed-effects. We retain bidders that have participated in five or less auctions. Standard errors are two-way clustered on two-digit zip codes and year, and are given in parenthesis. Significance: * p<0.1, ** p<0.05, *** p<0.01.

6 Discussion

6.1 Sensitivity

We examine how sensitive our results are to our chosen specification by including more control variables. In Table 8 we tabulate the regression results from using Model 3 (described above) on all five dependent variables when we include as variables the dummies 'Final auction of winner' and 'Absence of other bidders'. The former variable is unity for the bidder-auction combination in which a bid wins the auction. This bidder is observed with multiple other losing bids. The latter variable is unity when there are no other competitors in the bidding.

The pattern is intact. We retain the two first null hypotheses, those of no change in the choice of size and value of the units. Participation in more auctions is associated with increases in bids, bids relative to ask price, and bids relative to competing bids. The estimated coefficients for bids are statistically significant only for 'Auction number = 2' and 'Auction number = 3'. Three out of four estimated auction coefficients are statistically significant for 'Bids relative to ask price'. Two estimated coefficients are statistically significant on the 0.05-level and one on the 0.1-level for 'Relative bid position'. Including the addition control variables still implies non-rejection the null for size and ask price, while rejecting the null for bids, bids relative to ask price, and bids relative to competing bids.

The estimated coefficient of the dummy variable 'Final auction of winner' is negative for size, ask price, and nominal bid, although statistically significant only for ask price. The interpretation is that when a bid is the final bid of a winner, it tends to be the winning bid if the unit is smaller and the value lower. A bid tends to be a winning bid if the bid is higher relative to ask price and in the relative position to other bids.

The estimated coefficient of the dummy variable 'Absence of other bidders' is statistically significant and economically meaningful for multiple dependent variables. For size, the estimated coefficient is 2.67, which implies that when there are no other bidders, a bidder tends to bid on units that are 2.67 square meter larger. The intuition is that a bidder observes that no other bids arrive, the bidder may bid or not. The bidder displays a behavior that is associated with bidding in the case when there are no other bidders. Similarly, the estimated coefficient of 'Ask price' is statistically significant and large, 138.3. This means that when a bidder has no competitors they are observed to bid for more valuable units. NOK 138 300 amounts to 5.8 percent of the mean ask price. The estimated coefficient for nominal bid is -26.74 and statistically significant at a low significance level. The intuition is that the environment in which there are no competitors is associated with a smaller bid compared to the situation in which there are competitors. Similarly, the no competitor dummy is associated with a smaller bid relative to ask price and the estimated coefficient is -0.062. No competition is associated with a higher relative bid position. The intuition here is that absent other bidders, the bidder defines the maximum-minimum range of bids. The estimated coefficient of 0.029 summarizes bids bidders place when they are lone bidders, and essentially tells us how much such bidders tend to increase their bids to obtain an acceptance from the seller compared to their opening bids.

6.2 Robustness

6.2.1 Appraisal value

We examine the data that contain the appraisal value, and use the appraisal value instead of the ask price. In Table 9 we tabulate the regression results from using Model 3 above on all five dependent variables when we include as variables the dummies 'Final auction of winner' and 'Absence of other bidders'. The former variable is unity for the bidder-auction combination in which a bid wins the auction. This bidder is observed with multiple other losing bids. The latter variable is unity when there are no other competitors in the bidding.

The pattern is intact. We retain the two first null hypotheses, those of no change in the choice of size and value of the units. None of the ten coefficients of auction numbers are statistically significant for size and ask price.

There are 15 estimated coefficients in total for the variables 'Bid', 'Bid relative to ask price', and 'Relative bid position'. Seven estimated coefficients are statistically significant at a 5 percent significance level or a 1 percent significance level. One is statistically significant on the 1 percent level. For these three dependent variables, the estimated auction coefficients are statistically significant for 'Auction number = 2' and 'Auction number = 3'. The estimated coefficients increase in auction number. Thus, the estimated coefficients in this sensitivity analysis imply no rejection of the first two hypotheses and rejection of the last three hypotheses.

However, we do urge caution in interpreting results from this exercise as our findings are somewhat less clear than when we used ask price, not appraisal value. We conclude that the pattern is intact, albeit in somewhat weaker form.

6.2.2 Time between auctions

Our data comprise about 20 percent of the market, thus it is fathomable that there is unobserved heterogeneity between DNB-bidders and other bidders, and in addition, that DNB-bidders also participate in auctions arranged by other companies. These bidders would have a larger learning base than bidders that only participate in DNB-auctions, yet we would not know definitely that they have this expanded learning base. We suggest that a possible signal for a bidder that has participated in auctions other than DNB auctions could be extracted from the observed time between observed DNB auctions. Thus, we have constructed robustness checks based on observed bidder time periods between auctions. Specifically, we create sub-samples based on the longest pause between observed auction participation. First, we keep bidders with longest pauses at 20, 40, 60, or 80 days. Second, we keep bidders whose longest pauses are longer than 20, 40, 60, or 80 days.

We run a total of 40 regressions (4 segments, 2 sides, 5 hypotheses), so we cannot report all results.[6] The overall picture is that we do not obtain materially different results. However, we do observe a few, small differences. For example, we have estimated a negative coefficient

[6]Results are available upon request.

for auction number 4 in Model 3 for ask price when keeping those bidders with longest pauses above 20 and 40 days. This result in itself indicates that for this segment, we detect a reduction in the target value of the unit. Another example is that the coefficient estimates for the bidders' highest bids are larger but less significant than those in column 3 Table 5 when keeping repeat bidders with longer pauses. This is also the case for the coefficient estimates for bids relative to ask price (Table 6) and relative bid position (Table 7). We urge caution in interpreting these results as we would expect some deviations from the overall pattern when we run 40 regressions on sub-samples.[7]

[7]The regression results are available upon request.

Table 8: Sensitivity analysis. Regression (8) augmented by additional control variables

	Size (1)	Ask price (2)	Bid (3)	Bid rel. to ask price (4)	Rel. bid pos. (5)
Auction number = 2	-0.257	8.401	25.147***	0.006***	0.011**
	(0.319)	(6.661)	(6.843)	(0.002)	(0.005)
Auction number = 3	-0.072	21.107	49.391**	0.010***	0.028**
	(0.868)	(17.378)	(16.677)	(0.003)	(0.010)
Auction number = 4	-0.295	9.856	49.460	0.013	0.051*
	(1.489)	(27.867)	(36.159)	(0.008)	(0.029)
Auction number = 5	-0.838	-35.000	64.852	0.028***	0.092
	(2.284)	(39.102)	(45.360)	(0.006)	(0.054)
Final auction of winner	-0.549	-89.457***	-37.189	0.021***	0.321***
	(1.498)	(23.234)	(21.636)	(0.005)	(0.029)
Absence of other bidders	2.670***	138.299***	-26.740*	-0.062***	0.029**
	(0.868)	(17.208)	(12.596)	(0.005)	(0.013)
Tightness	0.125	11.244**	10.702	0.000	0.000
(daily buyers/sellers)	(0.293)	(5.052)	(6.202)	(0.001)	(0.002)
Thickness	-0.450	-7.126	6.400	0.006**	-0.001
(daily buyers+sellers)	(0.837)	(10.040)	(11.118)	(0.003)	(0.001)
Auction number = 2	-0.783	3.508	14.933	0.003	0.016
× Winner	(1.406)	(20.941)	(25.357)	(0.006)	(0.027)
Auction number = 3	-2.444	3.892	29.389	0.010	0.050
× Winner	(2.313)	(47.862)	(50.878)	(0.011)	(0.049)
Auction number = 4	0.025	57.729	123.421*	0.024**	0.063
× Winner	(2.926)	(60.944)	(66.169)	(0.010)	(0.059)
Auction number = 5	4.276	95.286	48.832	-0.006	-0.006
× Winner	(7.916)	(169.175)	(128.702)	(0.014)	(0.113)
Observations	28,849	35,201	35,201	35,201	34,906
Adjusted R^2	0.846	0.884	0.889	0.295	0.288
Bidder FE	✓	✓	✓	✓	✓
Intra-year calendar FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Notes: The table shows results of re-running (8) by regressing our five dependent variables on the auction number for the bidder-auction combination ba. In column (1), with size (in square meters) as the dependent variable, we choose to drop bidders if they are observed to bid on different unit types, e.g., first a detached house and then an apartment. If bidders are observed to win but still place bids afterwards, they are dropped from the sample. Ask price and bids are nominal values are measured in NOK 1,000. The relative bid position is defined as the ratio between a given bidder b's highest bid in auction a less the global minimum bid in auction a on the difference between the global maximum bid in auction a and the global minimum bid in auction a, $(\text{Highest bid}_{b,a} - \text{Minimum bid}_a)/(\text{Maximum bid}_a - \text{Minimum bid}_a)$. *Tightness* (*Thickness*) is the number of buyers divided by (added with) the number of sellers on the market. Non-repeat bidders are assumed to be active on the market within 270 days after they are observed placing bids and not winning, and repeat bidders are assumed active on the market between the first and last time they are observed. *Winner* is a dummy variable indicating whether the bidder is observed winning the final auction she participates in. This dummy is included as a helping variable but is not reported because of the bidder fixed-effects. *Final auction of winner* is a dummy variable indicating that final auction that the winner ultimately wins. *Absence of other bidders* is a dummy variable indicating whether the there are other bidders competing against the bidder in question, which by construction takes only value one in some of the final 'auctions' of the winners. *Bidder FE* are bidder fixed-effects, *Intra-year calendar FE* are seasonal monthly fixed effects, and *Year FE* are year fixed-effects. We retain bidders that have participated in five or less auctions. Standard errors are two-way clustered on two-digit zip codes and year, and are given in parenthesis. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Table 9: Robustness analysis. Re-run of regression (3), replacing ask price with appraisal and estimating on an appraisal subsample

	Size (1)	Appraisal value (2)	Bid (3)	Bid rel. to appr.value (4)	Rel. bid pos. (5)
Auction number = 2	0.136	0.776	26.583	0.008***	0.022***
	(0.817)	(13.301)	(17.142)	(0.002)	(0.006)
Auction number = 3	0.856	21.036**	44.636**	0.009	0.021
	(1.766)	(7.777)	(18.601)	(0.009)	(0.032)
Auction number = 4	2.886	-12.171	55.851**	0.030	0.110
	(3.624)	(48.557)	(18.019)	(0.024)	(0.085)
Auction number = 5	-8.154	-125.605	6.997	0.064***	0.181
	(8.486)	(205.993)	(171.021)	(0.018)	(0.309)
Tightness	0.659	14.534***	5.344	0.000	-0.032
(daily buyers/sellers)	(1.088)	(1.429)	(13.635)	(0.007)	(0.019)
Thickness	-0.774	-24.609	-0.666	0.010	0.037*
(daily buyers+sellers)	(1.355)	(31.460)	(24.403)	(0.006)	(0.017)
Observations	5,371	6,394	6,394	6,394	6,380
Adjusted R^2	0.844	0.844	0.860	0.149	0.093
Bidder FE	✓	✓	✓	✓	✓
Intra-year calendar FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Notes: The table shows results of re-running (3) by regressing our five dependent variables on the auction number for the bidder-auction combination ba, on a subsample with appraisals and replacing ask prices with appraisals in the ask and bid relative to ask models. We also re-define the auction number treating the subsample as isolated from the main sample, e.g., a bidder observed three times in the main sample but only the first and last of these bidder-auction instances have appraisals, the auction number in the appraisal subsample is 1 and 2 (not 1 and 3). In column (1), with size (in square meters) as the dependent variable, we choose to drop bidders if they are observed to bid on different unit types, e.g., first a detached house and then an apartment. If bidders are observed to win but still place bids afterwards, they are dropped from the sample. Ask price and bids are nominal values and divided by 1,000. The relative bid position is defined as the ratio between a given bidder b's highest bid in auction a less the global minimum bid in auction a on the difference between the global maximum bid in auction a and the global minimum bid in auction a, (Highest $\text{bid}_{b,a}$ − Minimum bid_a)/ (Maximum bid_a − Minimum bid_a). *Tightness* (*Thickness*) is the number of buyers divided by (added with) the number of sellers on the market. Non-repeat bidders are assumed to be active on the market within 270 days after they are observed placing bids and not winning, and repeat bidders are assumed active on the market between the first and last time they are observed. *Bidder FE* are bidder fixed-effects, *Intra-year calendar FE* are seasonal monthly fixed effects, and *Year FE* are year fixed-effects. We retain bidders that have participated in five or less auctions. Standard errors are two-way clustered on two-digit zip codes and year, and are given in parenthesis. Significance: * p<0.1, ** p<0.05, *** p<0.01.

7 Concluding remarks and implications

We present patterns that emerge when we study a novel data set on Norwegian bidding logs in housing auctions. The data set is sourced from Norway's second largest real estate firm, DNB Eiendom, and contains more than one million bids and about 200,000 housing transactions.

We find that repeat bidders do not seem to change behavior in terms of their targets (size and value), but do change behavior in terms of their tools (the way in which they bid). Participation in more auctions is associated with higher bids in nominal value, higher bids relative to the ask price, and more competitive bids in relation to other bids.

References

Anundsen, A. K., Larsen, E. R., and Sommervoll, D. E. (2020). Strategic price-setting and incentives in the housing market. *Housing Lab working papers*, 1.

Anundsen, A. K., Nenov, P., Larsen, E. R., and Sommervoll, D. E. (2022). Pricing and incentives in the housing market. *Housing Lab working papers*, 3.

Arefeva, A. (2017). How Auctions Amplify House-Price Fluctuations. Johns Hopkins Carey Business School Research Paper 17-12, Available at SSRN 2688859.

Arefeva, A. and Meng, D. (2020). How to set a deadline for auctioning a house. *Available at SSRN 3520197.*

Avery, C. (1998). Strategic jump bidding in english auctions. *The Review of Economic Studies*, 65(2):185–210.

Bikhchandani, S. and Riley, J. G. (1991). Equilibria in open common value auctions. *Journal of Economic Theory*, 53(1):101–130.

Börgers, T. and Dustman, C. (2005). Strange bids: Bidding behaviour in the united kingdom's third generation spectrum auction. *The Economic Journal*, 115:551–578.

Bucchianeri, G. W. and Minson, J. A. (2013). A homeowner's dilemma: Anchoring in residential real estate transactions. *The Review of Economic Behaviour and Organization*, 89:235–260.

Chow, Y. L., Hafalir, I. E., and Yavas, A. (2015). Auction versus negotiated sale: evidence from real estate sales. *Real Estate Economics*, 43(2):432–470.

Dodonova, A. (2017). Preemptive bidding and pareto efficiency in takeover auctions. *Economics Letters*, 159:214–216.

Ettinger, D. and Michelucci, F. (2016a). Creating a winner's curse via jump bids. *Review of Economic Design*, 20:173–186.

Ettinger, D. and Michelucci, F. (2016b). Hiding information in open auctions with jump bids. *The Economic Journal*, 126(594):1484–1502.

Ettinger, D. and Michelucci, F. (2019). Manipulating information revelation with reserve prices. *Annals of Economics and Statistics*, 133:87–92.

Genesove, D. and Hansen, J. (2023). Auctions and negotiations in housing price dynamics. *Review of Economics and Statistics*, pages 1–39.

Han, L. and Strange, W. C. (2014). Bidding wars for houses. *Real Estate Economics*, 42(1):1–32.

Horowitz, J. L. (1986). Bidding models of housing markets. *Journal of Urban Economics*, 20(2):168–190.

Hungria-Gunnelin, R. (2018). An analysis of auction strategies in apartment sales. *Journal of European Real Estate Research*.

Isaac, R. M., Salmon, T. C., and Zillante, A. (2007). A theory of jump bidding in ascending auctions. *Journal of Economic Behavior & Organization*, 62(1):144–164.

Levin, E. J. and Pryce, G. B. (2007). A statistical explanation for extreme bids in the house market. *Urban Studies*, 44(12):2339–2355.

Mateen, H., Qian, F., and Zhang, Y. (2021). The microstructure of the us housing market: evidence from millions of bargaining interactions. *Available at SSRN 3727150*.

Merlo, A. and Ortalo-Magne, F. (2004). Bargaining over residential real estate: evidence from england. *Journal of urban economics*, 56(2):192–216.

Milgrom, P. R. and Weber, R. J. (1982). A theory of auctions and competitive bidding. *Econometrica: Journal of the Econometric Society*, pages 1089–1122.

Smith, E. (2020). High and low activity spells in housing markets. *Review of Economic Dynamics*, 36:1–28.

Sommervoll, D. E. (2020). Jump bids in real estate auctions. *Journal of Housing Economics*, 49:101713.

Sønstebø, O. J., Olaussen, J. O., and Oust, A. (2021). Opening bid strategies in english auctions. *Journal of Real Estate Research*, 43(1):123–143.

A Bidding log data

A.1 Data description

Our data allow us to study behavioral patterns within and across housing auctions. The data set consists of Norwegian bidding log data provided by DNB Eiendom, which is the real estate agent arm of Norway's largest bank, DNB. DNB has a market share of about 20 percent. The data consist of bid-by-bid logs and include detailed information of the auction, e.g., the exact time (minute resolution) when bids are placed, by whom, under what conditions, and the value of the bid. We have accessed data in two rounds, which generated one data set from 2007 to 2017 and another that generated a data set from 2018 to 2021. When we merge these data, we retain bidder IDs, which are unique across auctions, but an ID from the 2007-2017 data set does not transfer to the 2018-2021 data set, and vice versa.

We start out with a data set in which we have ensured that there is no missing information on the sell price, the ask price, bids, or the size of the unit transacted. Then, we remove all transactions of units that are sold more than five times over our data period. We also truncate on the 1^{st} and 99^{th} percentiles of the sell price, ask price, and size. This truncation is done year-by-year and for nine different regions of Norway.[8]

We remove 'unserious' bids – bids that are less than 60 percent of the ask price. We also identify the 99^{th} percentile of the bid distribution, and remove the entire auction if at least one bid in the auction is greater than or equal to the 99^{th} percentile. This is done to rule out clerical errors and bids that are extreme.

Finally, we remove transactions that are recorded with a sell date that differs from the date of bid-acceptance, units for which the final bid is recorded as being accepted before it was placed, auctions for which any bid expires when or before it is placed. After these adjustments, our data set consists of 195,968 transactions and 1,271,741 bids.

[8]The regions consist of eight municipalities and the remaining sample: Asker, Bergen, Bærum, Fredrikstad, Lillehammer, Oslo, Skedsmo, Trondheim, and the remaining sample.

We use this data set to calculate a set of sale-specific measures: number of bidders, number of bids, number of bids per bidder, first bid-ask spread, highest-lowest bid spread, auction duration, sell-ask spread, ask, and size. These variables are summarized in the upper part of Table A.1, in which we also record the fraction of auctions that are owner-occupied and the fraction of apartments.

In the lower part of Table A.1, we show the distribution of a set of variables characterizing the sample: share of owner-occupied units, share of units located in Oslo, total number of bidders, total number of bids, and total number of sales.

The median sell-ask spread is zero, which suggests that the ask price has predictive power for the sell price. It does, however, have a right-tailed distribution, with a positive mean sell-ask spread.

Both the mean and median number of bidders are equal to 2, but there are many auctions with both a lower and a higher number of bidders. The highest number of bidders recorded in our data set is 34. At the auction-level, the median number of bids is 5 and the highest number of bids is 84. Each bidder typically makes four bids (75th pct.) or less, but in multiple cases they make more bids.

90 percent of the units in our data set are sold within 54 days of the list date, and the median TOM is 11 days.

While several bidding processes are completed quickly, some have long duration. If we denote the length of time from the first bid to the accepted bid as the bidding duration, we observe that more than 75 percent of bidding processes have a duration that is less than or equal to 3 days. We observe many cases in which there are relatively short expiration deadlines, and about 75 percent of the deadlines are two hours or less. Although some bidders extend bids with long deadlines, bids are countered quickly, and the median response-time is 15 minutes.

In most auctions, the value of the first bid is well below the ask price, and the mean spread between the opening bid and the ask price is 7 percent. Bid increments are typically relatively small, although there are cases in which increments are substantial – at the 90^{th} percentile, bids are increased by five percent relative to the previous bid.

At the median, the difference between the highest and the lowest bid of a bidder is seven percent, which suggests that bidders start their bidding well below their willingness-to-pay.

Table A.1: Summary statistics for bid-level sales data. Norway, 2007–2021

	10^{th} pct.	25^{th} pct.	Median	Mean	75^{th} pct.	90^{th} pct.
Sale-specific						
No. bidders	1.00	1.00	2.00	2.13	3.00	4.00
No. bids	1.00	2.00	5.00	6.49	9.00	14.00
No. bids per bidder	1.00	2.00	2.50	2.96	3.82	5.00
First-bid-ask spr. (in %)	-16.32	-10.78	-6.10	-6.90	-1.91	0.25
Highest-lowest bid spr. (in %)	2.13	3.92	7.14	9.23	12.00	18.43
Auction duration (in hours)	0.00	1.75	7.43	233.61	50.08	380.42
Sell-Ask spr. (in %)	-5.59	-2.61	0.00	2.12	5.56	12.71
Ask (in million NOK)	1.50	1.95	2.64	2.91	3.55	4.73
Size (in sqm.)	50.00	65.00	89.00	101.22	130.00	173.00
General						
Owner-occupied (in %)				68.94		
Oslo (in %)				18.39		
No. bidders				391,305		
No. bids				1,271,741		
No. sales				195,968		

Notes: The table shows summary statistics for sales-level data over the period 2007 – 2021. We have calculated the mean and median, in addition to the 10^{th}, 25^{th}, 75^{th}, and 90^{th} percentiles for each variable. All calculations are based on auction-logs from the real estate agent-firm DNB Eiendom. We include common debt in the computation of ask price.

In Table A.2 we present an example of bid with example variables included. In order to ensure anonymity, we have constructed a fictitious bid that maintains the essential elements of the information in our data.

A.2 Constructing market tightness and thickness

To construct market tightness and thickness, we need to calculate the number of buyers and sellers on the market at any given point in time, with a daily resolution. The number of buyers is calculated based on the observed number of bidders in the sample. Bidders observed participating in one auction is assumed to be active in the market 270 days after

Table A.2: Example bid

Variable name	Value	Description
Unit id	10101	Housing unit ID, consistent across sales
Assignment id	20202	Transaction ID
Auction Final bid accept time	2013-06-20 15:30	Time when the final bid was accepted
Auction Final bid expire	2013-06-21 13:20	Time of expiration of the final bid
Present bid time	2013-04-08 14:00	Time when the bid was received
Present bid expire	2013-04-08 15:00	Time of expiration of the bid
Present bid conditions	Yes	Conditions. For data 2007-2017
Unit size	93	Size of the housing unit, square meters
Unit type	owner-occupied	Housing unit type
Unit no. bedroom	3	Number of bedrooms
Unit ask	5,300,000	Ask price
Present bid value	5,200,000	Value of the bid
Present bidder no. bid	2	Bid number of bidder
Auction no. bidders	5	Total number of bidders in the auction
Auction no. bids	17	Total number of bids in the auction
Auction min bid	4,900,000	Lowest bid in the auction
Auction max bid	5,400,000	Highest bid in the auction

they are observed in the sample, and repeat bidders (observed participating in more than one auction) are assumed to be active between the first and the last time we observe them.

We calculate the number of sellers based on the number of observed unsold listings on the market in the sample. There is one challenge with this approach. The second data set, which contains bid logs from transactions that are finalized during the period 2018–2021, has a structural break in the variable that records listing dates. As a result, listing dates are not available for housing units sold between January and July 2018. Moreover, listing dates in the 2007–2017 sample are less precise than the listing dates in the 2018–2021 sample. This poses a challenge when calculating the number of housing units listed on the market at any given day for two reasons. First, units listed and sold during this time period drop out. Second, 2017 listings that are sold between January and July 2018 drops out. In total, when calculating the number of sellers on the market, it looks like the number of sellers drops sharply from about 1,000 to 0 from November 1 to December 31. Moreover, the volume of listings is zero until August 1 2018, where we observe 7 new listings. The number of observed listings then increases steadily during August. To deal with these issues, we start by counting the number of listings, then dropping the numbers between November 1 2017 and November 1 2018. The numbers between this period is simply replaced by a linear decline between the average number of listings in 2017 and 2019, leaving us with a patched series of number of sellers on the market.

Finally, market tightness is then calculated by dividing the daily number of buyer by the daily number of sellers on the market, while market thickness takes the sum of the daily buyers and daily sellers on the market.

Acknowledgements:

Housing Lab is partly funded by the Norwegian Ministry of Finance and the Norwegian Ministry of Local Government and Regional Development. Housing Lab also receives financial support from OBOS, Krogsveen, Sparebank1-Gruppen, and Pareto Bank. We are grateful for the financial support. All views expressed in our papers are the sole responsibility of Housing Lab, and do not necessarily represent the views of our sponsors. The authors are grateful to DNB Eiendom and Eiendomsverdi for auction and transaction data.

Authors:

André Kallåk Anundsen, Housing Lab, Oslo Metropolitan University, Norway; *andrekal@oslomet.no*

Andreas Benedictow, Housing Lab, Oslo Metropolitan University, Norway; *andreasb@oslomet.no*

Andreas E. Eriksen, Housing Lab, Oslo Metropolitan University and School of Economics and Business, Norwegian University of Life Sciences; *andrease@oslomet.no*

Erling Røed Larsen, Housing Lab, Oslo Metropolitan University, Norway; *erling.roed.larsen@oslomet.no*

Mikkel Walbækken, Sopra Steria, Oslo, Norway; *mikkel.walbakken@soprasteria.com*

ISSN: 2703-786X (Online)

OSLOMET

HOUSING LAB
Nasjonalt senter for boligmarkedsforskning