Getting more by asking for less?*

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Abstract

In auctions, a seller may strategically set a low ask price in an attempt to trigger more interest. More interest would increase the probability of multiple high bids and a bidding war. Does such a strategy actually work? We study a combination of data sets on repeat-sales, repeat-sellers, repeat-bids, and repeat-realtors sourced from Norwegian housing transactions, realtors' bid-logs, and official registers of ownership. More than fifty percent of the sellers offer an ask price that is below the estimated market value. Our results suggest that this is sub-optimal. A lower ask price leads to more bids, which in itself contributes to a higher sell price. However, a lower ask price price also anchors the opening bid in the auction, which has a negative impact on the sell price. We find that the anchoring effect dominates the increased-interest effect trigger by alower ask price. It does, however, appear to imply a higher sell-ask spread – a sales pitch for the real estate agent. We find that high-performing realtors recommend different ask price strategies than low-performing realtors. High-performing realtors tend not to be associated with transactions in which strategic ask prices have been used. Low-performing realtors, however, tend to be associated with such transactions. Moreover, a time-series regression among low-performing realtors shows that when a realtor in one year tends to use strategic ask prices, this realtor sees more business the next year. For high-performing realtors, there is no such association. Finally, we find that sellers who previously failed on the strategy of a low ask price learn that this is sub-optimal, and in consequence are less likely to offer a discount the next time they sell.

Keywords: *Strategic pricing; Auction dynamics; Housing market*

JEL classification:

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1 Introduction

With the advent of online advertising and digital auctions, the housing market started changing search techniques and matching outcomes. Now, more buyers can meet more sellers more easily than just a few years ago, and prospective bidders can even inspect the home without physical visits. They can make bids electronically and check for similar houses with a few clicks. This means that a seller faces more competition, but also that he may tap into a greater pool of buyers. In this new environment, a signaling game has emerged; with a competition on message among sellers over prospective buyers. The most powerful signal is the ask price. Set it too high and the seller scares away buyers. Set it too low and the seller tells the buyers that the unit is unattractive. This invites the idea that there is a sweet spot that just balances the anchoring effect with the herding effect. This article starts out by asking a simple question: Can a seller get a higher sell price by setting the ask price below what he thinks is the market value?

We demonstrate that the answer is “no”. The best a seller can do, is to set the ask price equal to the available estimate of market value, i.e. an appraisal value. Nevertheless, about fifty percent of sellers still use strategic ask prices; i.e., set an ask price that deviates from the appraisal value. This is the deeper and more challenging phenomenon this article seeks to explore. In fact, the possibility of strategic ask prices would have to imply questions. If they worked, why would not everybody use them? If they did not work, why would anybody use them?

We try to lay out the answers to this puzzle. One piece would have to involve the seller. Since people do not often sell houses, most of them are relatively inexperienced. Another piece deals with realtors. Since they sell many houses, they have experience, but they still vary in skills. A third piece is the prospective buyers behavior when they face a strategic ask price. They may or may not visit the public showing. They may or may not bid. They may or may not anchor their bid to the nominal level of the ask price.

To work out our multi-angle answers, we exploit a unique combination of Norwegian 2002-2018 data on repeat-sales, repeat-sellers, repeat-bidders, and repeat-realtors. The short answer is that experienced sellers tend not to use strategic ask prices and high-performing realtors advise sellers not to use them. Strategic ask prices are more frequently used by inexperienced sellers advised by low-performing realtors who have detected that using them is advantageous for next year’s business. This is not the case for high-performing realtors, who obtains higher sell prices without using strategic ask prices.

We arrive at these conclusions by taking the modern micro-econometric toolbox to a combination of data sources. In order to examine how the auction outcome variable, i.e. the sell price, is affected by choices for the ask price, we make use of three approaches. First, we gauge the outcome of the auction by comparing the sell price to the appraisal value. The appraisal value accounts for variables unobserved to the econometrician and allows us to define the strategic ask price. We inspect the sell price outcome for ask prices below, equal to, or greater than appraisal value. Then, we control for confounding factors that are not captured by the appraisal value. Unobserved heterogeneity of sellers may involve a self-selection sorting mechanism that makes one type of seller more prone to use strategic ask prices than others. This is troublesome if this propensity is associated with a tendency to accept bids differently than other types because the implication is that the underlying causality may not be linked to ask prices but seller types. We control for seller self-selection by using an exogenous variable, the appraisal value's proximity to a round number. The idea is based on the simple fact that the value of a given house moves through the value spectrum exogenously to the seller. This allows us to obtain a classical LATE-estimator.

Unobserved heterogeneity of units may involve time-invariable omitted variables mis-valued by the appraiser, e.g. view, or time-variable factors, e.g. renovation. We control for time-invariable unit fixed effects by following repeat-transactions [to be competed] and we control for potential time-variable effects by using ask price appreciation compared to a house price index to construct a proxy of time-variable fixed effects [to be competed].

These techniques allow us to test with a level of certainty whether strategic ask prices work or do not work. Our results [yet not fully complete], indicate that strategic ask prices draw a higher number of interested individuals to the public showing and are associated with a slightly shorter time-on-market, but strategic ask prices do not appear to lead to higher sell prices.

Since the practice of strategic ask prices is so commonplace, the deeper question is why sellers use them. To answer this question, one needs broad and deep data. To the best of our knowledge, we are the first to utilize a complete log of all bids in all auctions in a dataset that contains realtor and bidder identifier across auctions. We have obtained this dataset from the realtor arm of DNB, which is Norway's largest bank. This realtor, DNB Eiendom, has the largest market share in Norway. It includes more than one million bids made in several hundred thousand auctions during the period 2007-2018. These data allow us to test the hypothesis that high-performing realtors recommend different ask price strategies than low-performing realtors. We partition the data in two parts and use one part to classify high-/low-performing realtors into realtors who achieve a high/low sell price compared to appraisal value. From the other part of the dataset, we observe that high-performing realtors tend not to be associated with transactions in which strategic ask prices have been used. Low-performing realtors, however, tend to be associated with such transactions. Moreover, a time-series regression among low-performing realtors shows that when a realtor in one year tends to use strategic ask prices, this realtor sees more business the next year. For high-performing realtors, there is no such association.

We also study repeat-sellers by utilizing official registry information on buyers in Norway. Norway has one of the oldest registers of land and houses in the world, a system that goes back 800 years. Today, it is a complete list of properties and owners, mapped precisely by GPS coordinates. By following buyers over years, we construct a test on the segment of buyers who have sold one, two, or three times before while always using strategic ask prices. We classify the buyers who then sell for the second, third, or fourth time into groups that depend on the number of times in previous transactions the sell price was a success, i.e. the sell price was higher than appraisal value. The results show that when all previous sales using strategic ask prices led to a sell price above the appraisal value, the seller was more likely to use strategic ask price compared to the situations when not all previous sell prices were above appraisal value. Thus, it appears that among experienced sellers who have used strategic ask prices, the sellers with a successful history of using strategic ask prices tend to be more prone to use them again.

The third piece of the puzzle is bidder behavior when faced with strategic ask prices and when not. It appears that the anchoring effect is considerable. In fact, we see that the difference between the opening bid and the final, accepted bid is more or less the same, regardless of ask price or not. This means that if the strategic ask price is two percent below the appraisal, the resulting sell price is two percent below the counterfactual sell price of not using a strategic ask price. [This part is not complete and results are pending.]

This means that we are able to document that strategic ask prices do not work, but also that we can explain their existence. The explanation is a combination of a seller's inexperience, a realtor's individual pay-off matrix, and a bidder's tendency to be anchored to the nominal level of the ask price.

The contribution is empirical. We answer the question of whether strategic ask prices work by using a complete list of transactions in a whole country for many years, using several exogenous controls. We answer the question of ask price existence by looking into data on repeat-sellers and repeat-realtors. While an important part of the contribution is the novelty of the data, we also point to the institutional setting of the Norwegian housing market. It functions as a housing laboratory since it is set up as a classic auction. First, a seller advertises online and announces a date for a public showing. Interested parties inspect the unit on this showing and the bidding typically starts the next day. All bids are legally binding. The acceptance of a bid is legally binding. These activities take place on digital platforms and are quick and transparent.

The implications are heartening. The market sees through the false signal of a strategic ask price, a result that should allow policy makers to stay hands-off regulation. Our results also allow us to guide sellers and realtors to use fair ask prices and learn from high-performing realtors.

Our paper relates to several strands of the literature. First, Han and Strange (2014) show that "bidding wars" have become more frequent in the US housing market over the last 20 years. In the Norwegian housing market, such bidding wars occur frequently and our paper aims at studying how strategic pricing may affect auction dynamics. In a related paper, Han and Strange (2016) show that lowering the asking price leads to an increase in the number of bids. Our results corroborate this finding in that we document that a lower ask attracts more people to public showings and also results in more bids. However, we find that the effect that the lower ask has on the opening bid is stronger, so that a lower ask does not translate into a higher selling price.

Our paper also relates to the literature on anchoring, following the seminal study by Tversky and Kahneman (1974). A Google Scholar search shows 47,553 citing papers. Anchoring implies that the level of the ask price, or the initial bid, would tend to function as a nominal anchor of subsequent bids. This phenomenon has been demonstrated in many markets, e.g. art auctions (Beggs and Graddy (2009)) and DVD auctions on eBay (Simonsohn and Ariely (2008)). The latter study demonstrated how experienced bidders tend not to bid on auctions with low starting prices. They also studied another effect, "herding", which refers to the phenomenon that bidders herd into auctions with more existing bids. Anchoring may dominate herding, but it is an empirical question when this is the case. By now, the anchoring effect is well established, and it was also applied early to housing economics. For example, Northcraft and Neale (1987) showed how the anchoring effect was present in list prices. Recently, Bucchianeri and Minson (2013) discuss how listing strategies impact sale prices. Knowing that anchoring effects exist may also guide bidders since experienced bidders may take advantage of knowing how it works. Pownall and Wolk (2013) show that experience matters since participation in at least ten auctions is associated with 26 percent lower average bids. Bidders may not only strategically decide which auctions to participate in, or how to bid, they may also form plans over which sellers they visit. This idea goes back to the study by Mcafee (1993), who constructed a dynamic model with many sellers and many buyers in which he finds an equilibrium where sellers hold identical auctions and buyers randomize over which seller they visit. In general, that nominal effects may take place is well studying. Perhaps this was clearest showed in the housing literature by the loss aversion study by Genesove and Mayer (2001). Our finding that a lowering of the ask curbs the opening bid in housing auctions suggest a link between the asking price and the reservation price of prospective buyers.

How to set ask prices is the central question in another stream. It is likely that sellers start out by contemplating their reservation price, but their ask price may not be identical to it. Horowitz (1992), for example, constructs a model that can explain why a seller's ask price may deviate from his reservation price. Taylor (1999) shows that it is possible that sellers may want to set both a high and low ask price, depending on conditions. He examines how the seller of a house may be able to manipulate the quality impression of a prospective buyer through an ask price strategy. His model demonstrates that sellers of high-quality do worst when inspection outcomes are not public and the price history not observable. There are mistakes to be made. Knight (2002) shows that mis-pricing of the unit when setting the initial ask price is costly in time and money. Moreover, when the value of the unit is close to a round number, a seller needs to think about how the ask price should be set since Beracha and Seiler (2014) find that the most effective pricing strategy for the seller is to use an ask price that is just below a round number. It could also be that the seller does not know what the demand is for the type of unit he is selling. Herrin et al. (2004) examine ask prices under demand uncertainty and to what extent that implies price cutting. They find that owners who are highly motivated to sell are more flexible in price strategies. Haurin et al. (2013) show that sellers appear to select strategies depending on the strength of the market. They find support for claiming that sellers switch to auction-like mechanism in booms. Guren (2018) demonstrates that setting an ask price above the average-priced house reduces the sales probability while setting the ask price below the average-priced house only marginally increases the sale probability. Liu and van der Vlist (2019) compare ask price strategies among home-owners who expect to sell with capital loss with home-owners do expect to sell with capital gains. The former set ask price ten percent higher. This indicates that a seller needs to know his market and who are his potential bidders, clearly demonstrated by the almost four percent excess sell price realtors were able to acquire when they sold themselves (Levitt and Syverson (2008)). Agarwal and Song (2015) show that real estate agents, when they buy themselves, are able to buy otherwise identical units at a price which is about two percent lowers than other buyers. This is indicative of the strategy room in which knowledgeable agents can navigate. Merlo et al. (2015) study the multi-faceted home-selling problem. They start out by looking at the first step, whether to use a realtor or not, then choose an ask price, and finally accept or reject offers. They show that a very small menu cost, ten thousandths of one percent of house value, generates a high degree of price stickiness. In other words, sellers tend to keep their initial ask price. They suggest the sellers want to anchor the subsequent negotiations, because they do not appear to be unwilling to sell below the ask price. Our findings suggest that decisions on the asking price are related to both seller's experience, a realtor's individual pay-off matrix, and a bidder's tendency to be anchored to the nominal level of the ask price.

The outline of the paper is this. The next section gives a taste of the literature. Then we outline the theory, present our data, and describe the institutional setting of the Norwegian housing market. We then present our results on the tests of the outcomes of strategic ask prices and the explanations for their existence. Subsequently, we show our sensitivity and robustness checks before we offer concluding remarks and policy implications. In an appendix, we include more results.

2 A skeleton model for the potential efficacy of a strategic low ask

The ask in Norwegian real estate auctions are not binding in any legal way. If the highest bid is equal to the ask, the seller may or may not accept the bid. In this sense the ask may be considered cheap talk signaling, and interested parties should wisely ignore the ask price. In the model we present below, we interpret the the difference between the valuation and the ask, $P_v - P_a$, as a signal of a potential rebate. It must be stressed that rushed sales (xxxref) tend to sell at a considerable discount (5 percent check), and sellers that are in a hurry due to for example job relocation could offer the rushed sale rebate in advance, to boost interest. If the acclaimed rebate materialize or not, is immaterial for the first stage in the selling process, getting interested parties to the viewing. The important thing is that enough prospective buyers are attracted by the potential rebate, and some consider the dwelling attractive enough to place bids, and hopefully surpass the ask and maybe the valuation.

To give these ideas some purchase consider the following model:

The offered rebate:

$$R(P_a) = P_v - P_a, \tag{1}$$

where P_v is the valuation, P_a is the ask.

The number of bidders is given by a Poisson distribution:

$$P(k \text{ number of bidders}) = \frac{\lambda^k e^{-\lambda}}{k!}, \tag{2}$$

where $\lambda = \lambda(R(P_a))$ and λ is increasing in the rebate signal $R(P_a)$

The bid of bidder i:

$$B_i = B_i(P_a), \tag{3}$$

where B_i is decreasing in P_a.

The transaction price:

$$P_t = \max(B_1, \ldots, B_k), \tag{4}$$

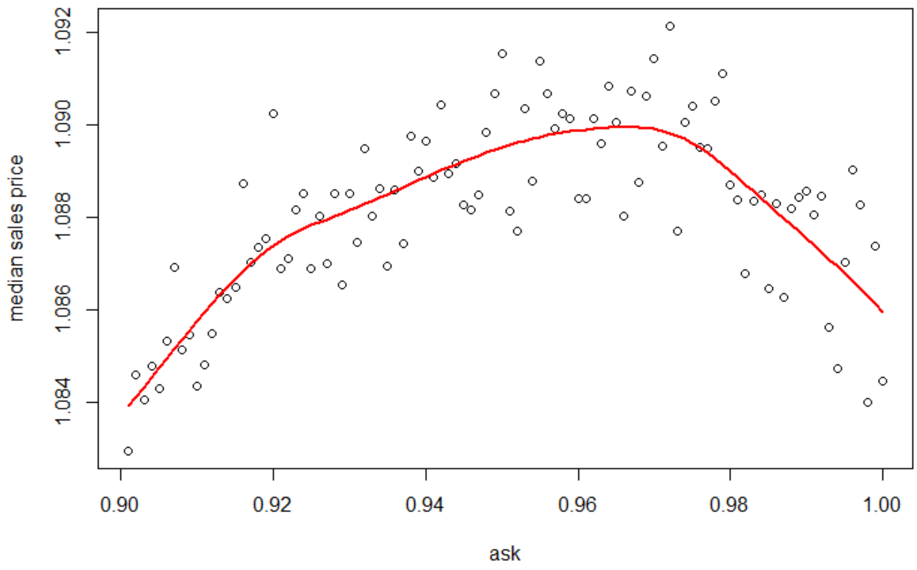
where B_i is the highest bid of bidder i[1].

[1] This applies only in the case where P_t exceeds the seller's reservation price P_r.

This model captures two opposing effects. First the positive effect of offering a rebate on the number of bidders. Second the anchoring effect of a low ask on bids. In mathematical terms $P_t = P_t(k(P_a)), P_a)$ is increasing in the first argument $k(P_a)$ and decreasing in the second (P_a). As the first argument k is decreasing in P_a, we get two offsetting effects of lowering P_a: A positive effect regarding the number of bidders, but the bids gets curbed. The relative strength may vary with $R(P_a)$.

One numeric example is given below:[2]

Figure 1: Example of toy model run...



[2]Technical detail of the simulation that give this plot: For every ask P_a a sample of 10 000 auctions are drawn. The number of bidders in each auctions is drawn from a Poisson distribution with $\lambda = 3 + 16 \times \frac{p_v - p_a}{p_v}$. In other words in absence of a strategic ask on average three bidders are expected. If the ask is set 6.25 percent lower than the valuation (here normalized to 1) on average one more bidder is expected. In the case of two or more bidders, the transaction price is the second highest willingness to pay. The willingness to pay is drawn from a normal distribution with mean $\frac{p_v + p_a}{2} + 0.10$. In other words the willingness to pay is on average the average of the ask and the valuation plus 10 percent of the valuation. In the case of one or zero bidders, the house is sold at 95 percent of the valuation. It must be stressed that all of these choices are semi-arbitrary and is only intended to serve as an illustration of a combined bidder and anchoring effect. The main point is that for some strategic asks the effect on the number of bidders and their bids higher are than the anchoring effect, thus pave way for a strategic low ask that harvest higher transaction prices. It is interesting to note. that the simulation shows that even in the case of 10 000 bidding rounds there is quite a noisy relationship between the ask and the medium transaction price.

3 Institutional details, data and empirical approach

3.1 Institutional details

The selling process

In Figure 2, we summarize the selling process in Norway. Until 2016, a person who decideded to sell to sell his property, obtained an appraisal value from an appraiser. From 2016 onwards, the value estimate is made by the realtor. The appraiser would inspect the home prior to the advertisement and write a technical report about the general condition of the unit. The report would include description of the material standard, technical issues, and other information. For example, the appraiser would identify a need for drainage, measures of water pressure, and potential problems with moist. The report would describe the age of bathrooms and washing rooms and detail if and when renovation of different rooms were undertaken. The report could also include information on view, sun light exposure (balcony facing west versus east), air quality, proximity to grocery stores, and kindergartens. Based on the inspection, the appraiser would make an estimate of the market value. This estimate would take into account both the market conditions and the technical elements of the unit. When a home was listed for sale, the appraisal price and the technical report is common knowledge to both sellers and buyers. After 2016, these elements were handled by the realtor, who would acquire the necessary information and in addition make use of his market knowledge in describing the market conditions.

Having collected estimate of the market value, either from an appraiser or from a realtor, , the seller makes a decision - in collaboration with the realtor – on the asking price. The seller may choose to set an ask that is lower than, equal to, or higher than the estimate of the market value. For data before 2016, this would be the appraisal value. The ask price is a signal and the seller is not obliged to accept a bid at, or even above, the ask price, although the trade norms state that in general bids above ask price should generally be accepted However, the ask price does not legally function as a ceiling or a floor, and the seller may choose the ask price strategically in an attempt to affect the outcome of the auction.

Having decided on the ask price, the seller posts the house for sale, typically using the nationwide online service Finn.no and national and local newspapers. Figure 3 shows that most units are announced for sale on Fridays. This is especially common in the capital, Oslo, although local variation sometimes imply different frequencies. In the ad, the seller also states when there will be a public showing of the unit, which typically happens on a weekend the week after posting the ad. The auction commences on the first workday that follows the last showing, but it is possible to extend bids prior to the public showing. It is legal, and common, to make conditional bids. Usually, the conditions involve an expiration time, e.g. 1 hour or noon the next day, but conditions may be made on access to financing.

Figure 2: The selling process

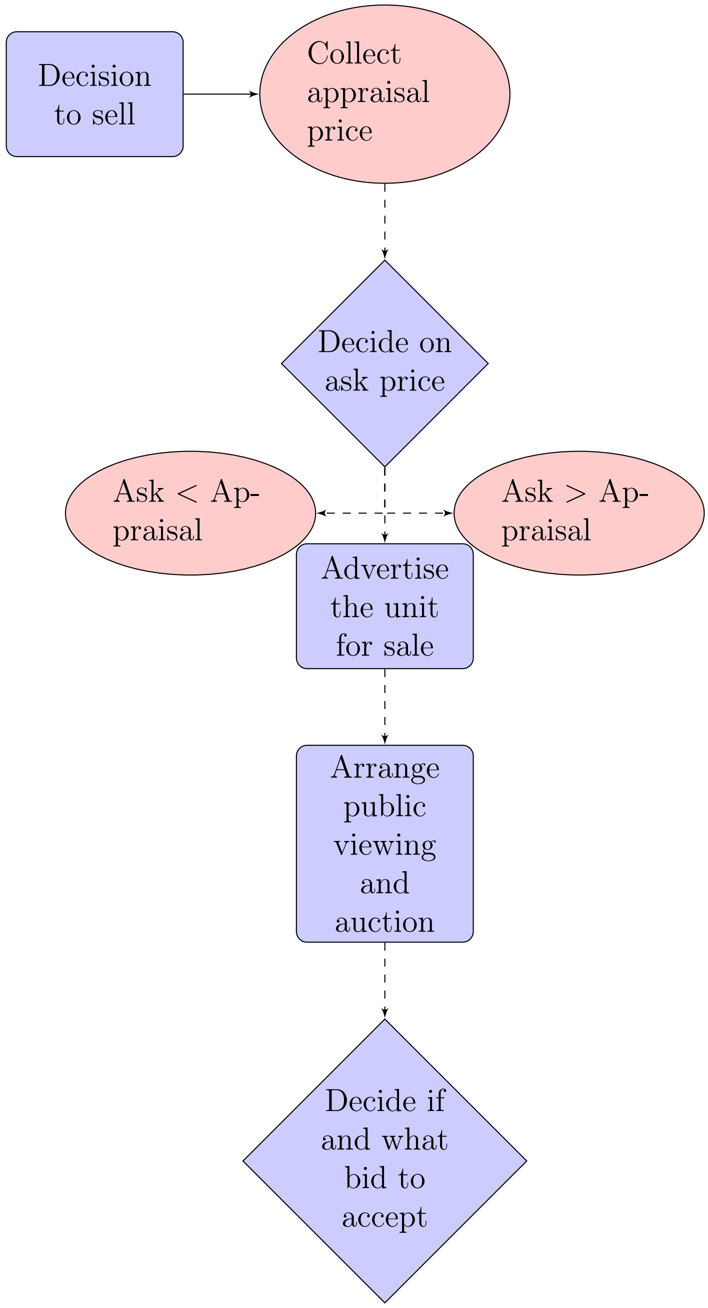
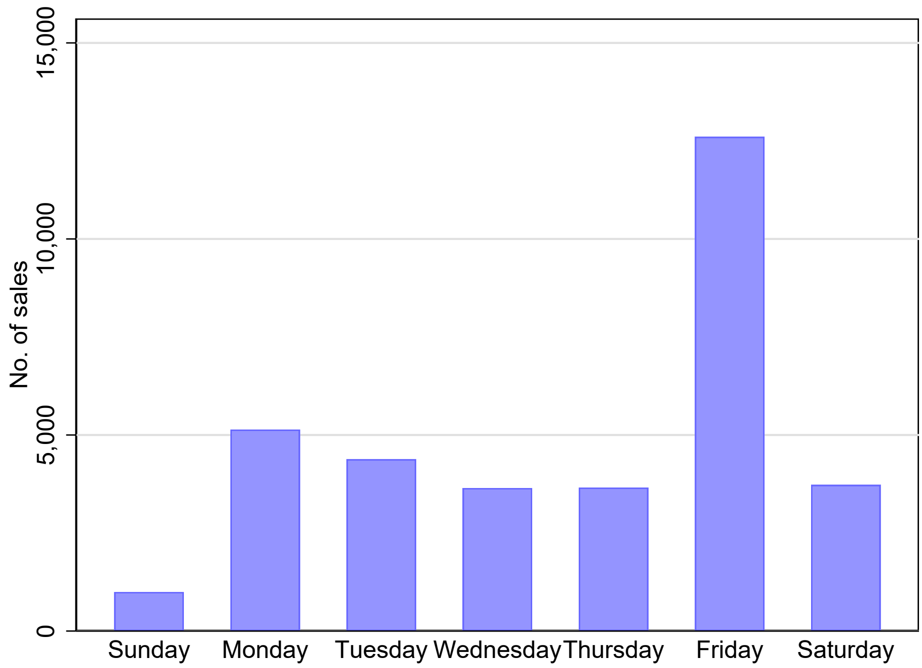


Figure 3: Days that units are advertised for sale



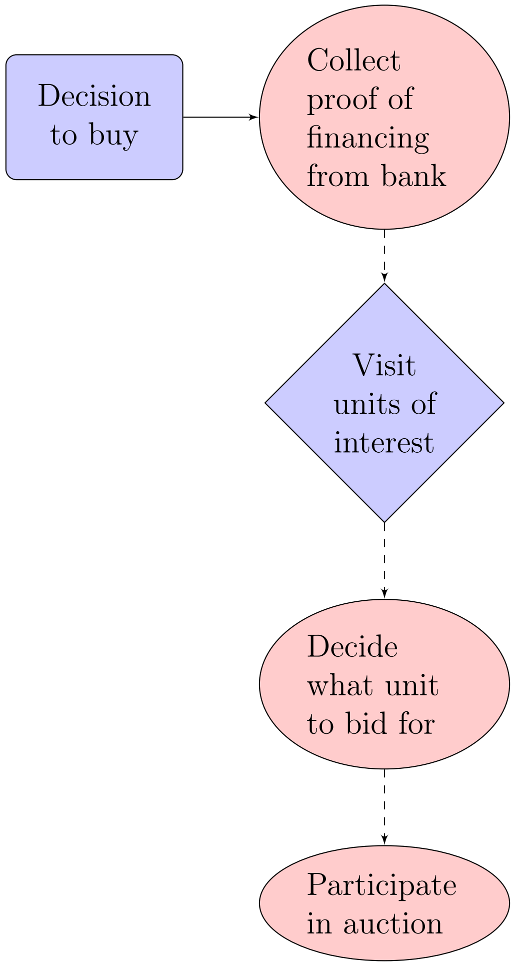
The buying process

In Figure 4, we summarize the process of buying. A buyer first goes to his bank to collect proof of financing. The buyer documents his income, other debts, wealth position, his status as married, single, or living with a partnre. The bank assesses the financial ability of the applicant and compares its estimate with legal requirements. Conditional on financing, the search process begins. Note that the buyer does not hire a separate real estate agent and that the proof of financing is not contingent on buying a particular unit – it reflects the maximum loan. Loan-to-value is calculated based on actual selling prices, and not on the appraisal value. The proof of financing is typically valid for three months and during this period, the buyervisits units of interest and within budget. Having found a unit of interest, the buyer places his bid. Since each and every bid is legally binding, most buyers only bid for one unit at the time.

The auction

The sale of a unit takes place through an ascending bid English auction. The bids take place by telephone, fax, or electronic submission using digital platforms, and the realtor informs the participants (both the active and the inactive) of developments in the auction. Each and every bid is legally binding and each and every acceptance of bid is legally binding. When a bidder makes his first bid, he typically submits the statement of financing that documents proof of access to funding, although this practice is cloaked in some technicalities since the seller does not want to inform the realtor of the upper limit of his bidding capacity. The seller has the option to decline all bids. When the auction

Figure 4: The buying process



is over, every participant in the auction is entitled to see the bidding log, which provides an overview of all the bids that were placed during the auction.

3.2 Data and descriptive statistics

The data we consider are collected from several sources, and are divided in three broad categories; transaction level data for every single publicly registered housing sale since 2002, detailed auction data on every single auction managed by real estate agents at one of Norway's largest real estate companies since 2007, and survey data on the customers of the largest Norwegian bank.

Transaction data

Our transaction level data have been acquired from the firm Eiendomsverdi AS, a private firm that collects data from realtors, official records, and Finn.no (a Norwegian classified advertisement web-site) and combines such data with other information. Eiendomsverdi specializes in constructing automated valuation methods that deliver price assessments for commercial banks and realtors in real time. Commercial data are merged with official records and the resulting data set is a comprehensive register of publicly registered housing transactions in Norway between January 1st, 2002 and December 31st, 2016, and contains information on both the transaction and the unit. Transaction data comprise date of accepted bid, date of announcement of unit for sale, ask price, selling price, and appraisal price made by an independent appraiser. Unit data include unique ID, address, GPS coordinates, size, number of rooms, number of bedrooms, floor, and other attributes.

Our analysis is confined to the capital city of Oslo, which gives a total of $59,253$ transactions. Table 1 summarizes the data for the full sample, whereas Table 2 shows the data for the sub-sample of units where the asking price is lower than the appraisal price.

Our sample consists of nearly 80 percent apartments and the median selling price is NOK 2,900,000. Units are sold relatively fast, with a mean time-on-market of only 15 days. At the median, there is a positive sell-ask spread, suggesting that the ask is not an unbiased predictor of the selling price. In contrast, the sell-appraisal spread is zero at the median.

Comparing the full sample to the discounted units, it is clear that discounted units sell with a lower sell-appraisal spread. In general, units that are sold with a discount are smaller and cheaper, and apartments are represented (somewhat) more often than detached houses. To explore the sensitivity of our results to this variation, we check for robustness to estimation in sub-samples with apartments only, small versus large units and different price segments.

Table 1: Summary statistics for transaction level data, full sample.

Variable	10th	25th	Mean	Median	75th	90th
Sell	1550000	2050000	3487381	2900000	4300000	6150000
Ask	1500000	1990000	3418572	2850000	4200000	5990000
Appraisal	1550000	2050000	3470955	2900000	4250000	6100000
Sell-Ask	-3.51	-.82	2.4	1.82	5.88	8.91
Sell-Appraisal	-5.58	-2.67	.71	0	4.38	7.41
Size	44	55	89	74	108	158
TOM	7	9	15.5	11	18	33
Apartment			80.3			
Detached			7.73			
Semi Detached			5.62			
Row house			6.3			
No. observations		59,253				

Auction data

In addition to the transaction data, we have obtained detailed auction data from one of the largest real estate agencies in Norway, DNB-Eiendom – a part of the largest Norwegian Bank, DNB. The data cover the period 2007–2017, and include very detailed information on every single bid placed in every single auction that resulted in a sale and that was arranged by DNB-Eiendom over this period. We have information on each bid, including a unique bidder id, the size of each bid, when the bid is placed (at the minute), the

Table 2: Summary statistics for transaction level data, discounted units only.

Variable	10th	25th	Mean	Median	75th	90th
Sell	1560000	2000000	3306920	2815000	4010000	5700000
Ask	1490000	1950000	3217516	2750000	3950000	5500000
Appraisal	1550000	2000000	3315310	2800000	4000000	5700000
Sell-Ask	-2.81	0	3.17	2.51	6.77	10.1
Sell-Appraisal	-6.45	-3.66	.0163	0	3.75	7.1
Size	43	54	83.8	70	100	144
TOM	7	9	16.2	11	19	35
Apartment			83.7			
Detached			5.85			
Semi Detached			4.62			
Row house			5.86			
No. observations		31,739				

expiration of the bid (at the minute), asking price, appraisal price, attributes of the unit, number of people that have shown an interest at the public viewing and a unique realtor id for the agent being responsible for the auction. Table 3 summarizes some of the variables that we construct based on the auction data.

At the median, an auction has two bidders and a six bids. The opening bid is typically lower than both the ask price and the sell price, and the median incremental price increase is NOK 30,000. The auctions are speedy – most bids have an expiration within an hour and – at the median – a bid is countered by another bidder within a little more than 10 minutes.

Survey data

To better understand how people perceive the role of the asking price, we asked a few questions to 2,500 customers of the largest Norwegian bank, DNB. Our questions were included in a larger survey on the housing conducted by DNB in collaboration with Ipsos. The larger survey has been conducted on a quarterly basis since 2013, and our questions were included in the 2018Q2 edition. In addition to demographic details (gender, age, income, city, education, marital status), people are asked various questions about the housing market, such as the likelihood of moving, house price expectations etc. There are two questions in the original survey that are particularly relevant also for our purpose; namely people's expectations about selling and purchase prices relative to the asking price, and how important people perceive the real estate agent to be for the final selling price. The questions we asked are directly related to the role of the asking price itself, and whether people believe it to affect auction dynamics. While we will refer to the survey results throughout the paper, detailed results are reported in Appendix A.

1. Maybe take out 1–2 questions here, that we think are particularly relevant?

Table 3: Summary statistics for auction level data.

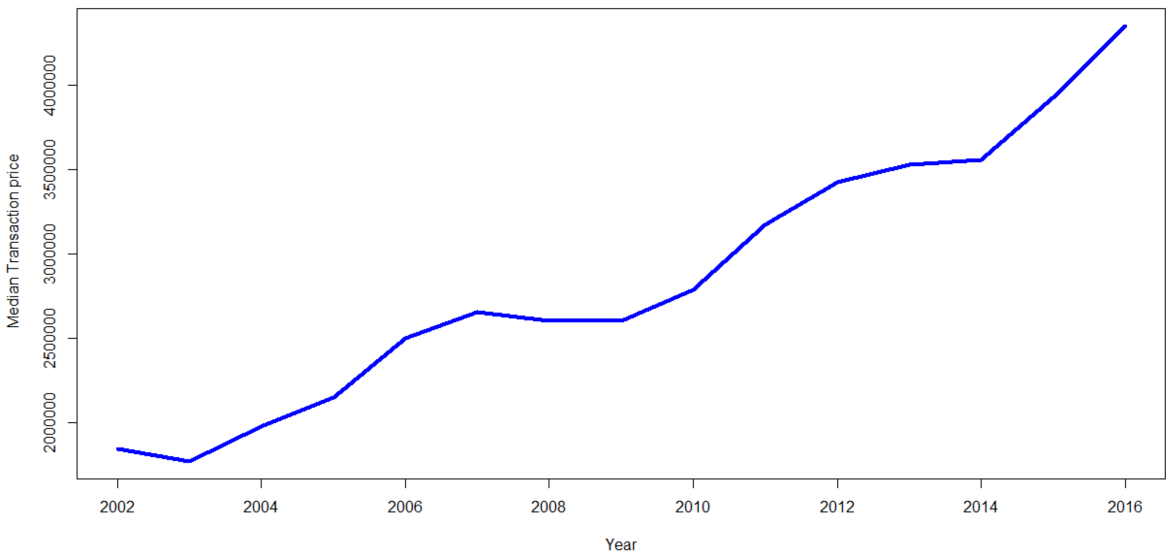
Variable	10th	25th	Mean	Median	75th	90th
Across auctions:						
No. bidders	1	1	2.81	2	4	5
No. bids	1	3	8.61	6	12	18
No. bids per bidder	1	2	3.02	2.67	4	5
No. bidders $\geq$ 2 bids	0	1	1.93	2	3	4
No. bidders $\geq$ 3 bids	0	0	1.36	1	2	3
Perc. dist. b/w opening bid and ask	-14.2	-9.7	-5.1	-5.19	0	1.78
Perc. dist. b/w opening bid and sell	-20	-14.4	-9.62	-8.72	-3.85	0
TOM	8	11	31.7	18	33	67
Across bidders:						
Price increase	10,000	15,000	101,165	30,000	60,000	150,000
Time to next bid (min.)	1.83	4.6	4,893	11.8	38.8	418
Time to expiry (min.)	12.6	22.4	79,262	35	118	569
No. auctions			30,383			
No. bids			261,263			

3.3 Stylized facts

National developments

The period between 2002 and 2016 has largely been about house appreciation. Figure 5 shows the evolution of the median house price in Oslo since 2002. **Si mer?**

Figure 5: Median house price by year



Discount frequencies

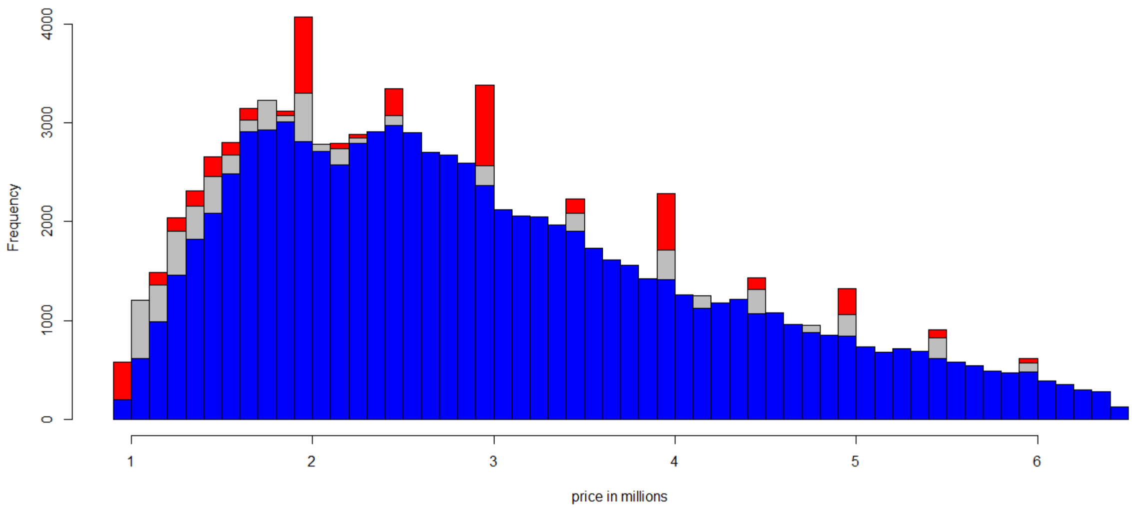
Before putting a house out for sale, the seller needs to decide on the ask price. An obvious option is to set the ask equal to the valuation. Many sellers do this. As seen from Table 4, about 46 percent sets the ask equal to the valuation. The sellers that avert from this option are unevenly divided into those who ask for less (53 percent) and those who ask for more (1 percent).

Table 4: Frequencies of asking price below, at and above the appraisal price.

Number of observations	Less	Equal	More
$59,746$	53.1	46.1	0.8

Figure 6 gives the distribution of valuation (grey), ask (red), and sell (blue) prices. There is a striking difference between the distribution of ask prices and the distribution of valuations and transaction prices. The ask is heavily concentrated below full millions, indicating that people are using a nine-ending pricing strategy. The valuations and the sales price do not display the same pattern.

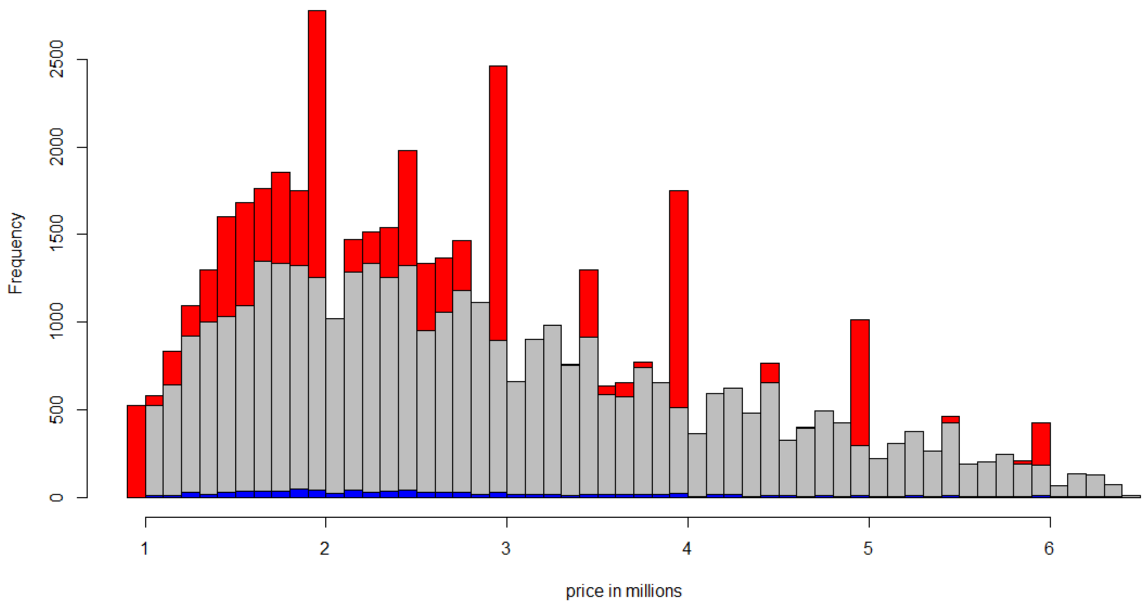
Figure 6: The distribution of asks (red), valuations (grey) and transaction price (blue): (lower: red, equal: grey, higher: blue)



This spiked distribution of asks relative to the valuation is further highlighted in Figure 7, which shows the distribution of asks that are lower (red), equal to (grey) and higher (blue) than the externally set appraisal price. We see that setting the ask equal to the valuation is common for every price bracket. The low ask however shows has a heavy concentration around just below full millions, consistent with a nine-ending price strategy.

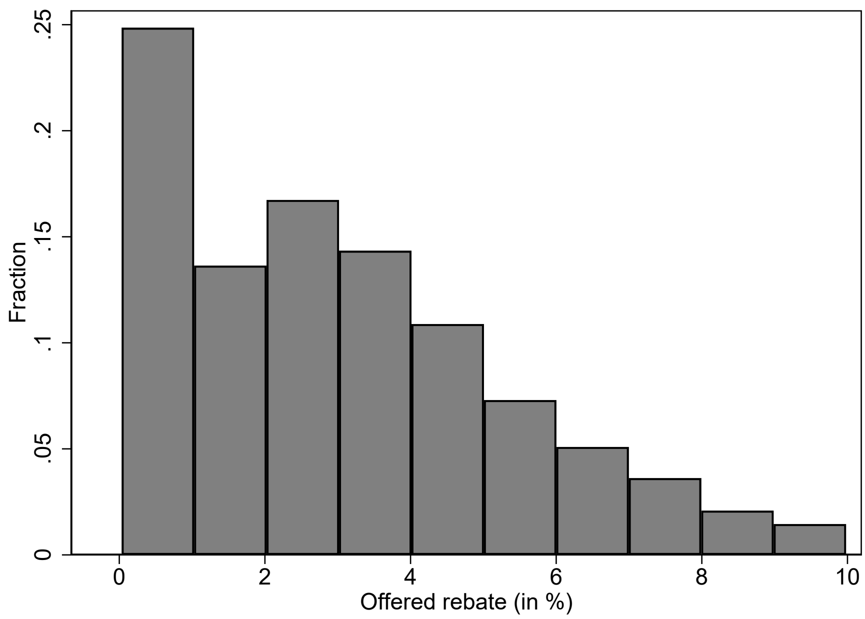
In Figure 8, we plot the distribution of percentage discounts (relative to the appraisal) offered by sellers that set the ask lower than the appraisal. It is clear that a majority of

Figure 7: The distribution of asks: (lower: red, equal: grey, higher: blue)



the discounts are relatively small (less than three percent), but almost 25 percent of the discounts are greater than 3 percent.

Figure 8: The distribution of nominal discounts



3.4 Empirical approach

Baseline specification to study the effect on auction outcomes

We are interested in how a lowering of the ask price affects auction outcomes and auction dynamics. For the auction outcomes, we use the full transaction data set, and our main unit and time fixed effect specification for:

$$\text{Auction outcome}_{i,j,t} = \left\{ \frac{Sell_{i,j,t} - Appraisal_{i,j,t}}{Appraisal_{i,j,t}}, log(TOM)_{i,j,t}, \frac{Ask_{i,j,t} - Appraisal_{i,j,t}}{Appraisal_{i,j,t}} \right\}$$

is given by:

$$\text{Auction outcome}_{i,j,t} = \eta_i + \alpha_t + \gamma_j + \beta AskDev_{i,t,j} + Controls + \varepsilon_{i,t,j} \tag{5}$$

in which i indexes the unit that is sold in local market j at time t, with α_t and γ_j being time and zip-code fixed effects. A sub-sample of the units are transacted multiple times, allowing us also to control for unit fixed effects, η_i. For unit fixed effect regressions, we do not use unit-specific controls as they are linearly dependent, but we include them in the specification so to indicate runs of simple OLS. The set of controls includes: size of the unit, house type (dummies for apartment, detached, semi-detached or row house), ownership type (coop versus owner occupied), building year fixed effects and the logarithm of the appraisal value.

Setup to study auction dynamics

To study the effect on several auction outcomes, we consider the following specification:

$$Log(\text{Auction variable})_{i,t,j,k} = \alpha_t + \gamma_j + \eta_k + \beta Ask_{i,t,j,k} + Controls + \varepsilon_{i,t,j,k}$$

in which index i is the unit transacted at time t in area j by realtor k working at realtor office s. We look at several variables to measure auction dynamics; Interest at viewing, No. bids, No. bidders, No. bids per bidder, Auction length and the difference between the opening bid and the appraisal value. Again, controls only apply for OLS, not for unit fixed effect regressions.

A LATE setup

In Section 3.3, we saw that low ask price are concentrated just below the full million demarcations. In other words, sellers seem to opt for a nine-ending price strategy. As an alternative test of the low-ask strategy, we adopt a standard local average treatment estimation as described in Angrist and Pischke (2014). The intuition is the following: A valuation just above a full million, serves as an invitation to set a nine-ending ask. The invitation to be treated does not imply that the seller is treated. Moreover, sellers receiving a valuation that is not close to the full million may also set a nine-ending ask.

The premise for establishing causal effects is that the invitation to be treated, in our case having an appraisal value just above the full million demarcation line, is exogenous.

Moreover, the invitation to treat should translate into treatment for a substantial fraction of the invited group. This fraction needs also to be substantially higher than the treated in the non-invited group. Furthermore, we need to rule out that seller or house-specific factors correlate with appraisal values being just above a full million. The key factor in our empirical approach is the exogeneity of the appraisal value. The owner has no way of knowing whether the valuation would be just above or just below a given million nor can a seller influence the market price level. The nominal development of house prices over our sample period ensures that most houses have passed through the full million demarcation lines at least once. In other words, a substantial share of houses did pass through a nine-ending window of opportunity.

Formally, the instrument, Z_i, is a dummy variable that takes the value one if the valuation is just above the full million demarcation line. We define just above one million as an appraisal value that comes in the interval $(m, m + 100000)$, where m is an integer number of millions. For instance, an appraisal value of $4,050,000$ gives $Z = 1$, whereas an appraisal value of $4,400,000$ gives $Z = 0$.

Let the treatment variable, D_i, be a dummy variable which is equal to one if the ask price is nine-ending, and zero otherwise. The outcome variable is denoted by Y_i and measures the same set of variables as described above. We call this variable the score for short. If a nine-ending ask price, made possible by a valuation just above a full million, causes a higher transaction price, scores will be higher for the treated group.

The local average treatment effect (LATE) of setting a nine-ending ask is given by:

$$\lambda = \frac{\rho}{\phi} = \frac{E[D_i|Z_i = 1] - E[D_i|Z_i = 0]}{E[Y_i|Z_i = 1] - E[Y_i|Z_i = 0]} \tag{6}$$

where $E[D_i|Z_i = 1] - E[D_i|Z_i = 0]$ is the difference of rates of nine-ending asks in the two groups, while $E[Y_i|Z_i = 1] - E[Y_i|Z_i = 0]$ is the average difference in the score between the two groups:

We are not concerned with setting the ask price if the appraisal value is just below a full million. To avoid confounding factors related to such pricing mechanisms, our analysis is confined to the subset of houses having appraisal values in the interval $[m, m + 500000]$. Thus, we consider houses with in which appraisal values would be rounded down, if rounded to the nearest million.

4 Empirical results on auction outcomes

4.1 Baseline Specification

Selling price relative to appraisal

Table 5 shows the estimated effect of the ask deviation (the ask-appraisal spread) on the sell deviation (the sell-appraisal spread). We start by estimating the simplest specification, with no control variables. Results are reported in Column 1. Then, we gradually add more controls. In Column 5, we consider a sub-sample of units that are transacted multiple times, so that we can control for unobserved heterogeneity through the inclusion of unit-fixed effects. Results are very similar across specifications and paint the same general picture; a lower ask price relative to the appraisal value leads to a lower sell price compared to the appraisal value. Asking for less therefore leads to a loss for the seller.

Table 5: Regressing $\frac{Sell_{i,j,t} - Appraisal_{i,j,t}}{Appraisal_{i,j,t}}$ on $\frac{Ask_{i,j,t} - Appraisal_{i,j,t}}{Appraisal_{i,j,t}}$. Oslo, 2002-2016

	(1)	(2)	(3)	(4)	(5)
Ask dev.	0.51***	0.53***	0.53***	0.52***	0.46***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	59253	59253	59253	59253	27425
R2	0.0637	0.0837	0.159	0.165	0.183
Size		✓	✓	✓	
House type FE		✓	✓	✓	
Ownership type FE		✓	✓	✓	
Building year FE		✓	✓	✓	
Zip code FE			✓	✓	✓
Time FE			✓	✓	✓
Appraisal				✓	✓
Unit FE					✓

Time-on-market

One reason for setting the ask price low could be the intention to sell fast. If we assume that setting the ask price low is a credible signal of the intention to sell fast and with a discount (if necessary), we would expect to see shorter time-on-market (TOM) for low ask prices.

Table 6 summarizes the estimated effects of ask price deviations on the time-on-market. Again, we start with the simplest specification and proceed to add more control variables. The final column report estimates for the sub-sample of units that have been transacted multiple times – allowing us to control for unit-fixed effects. A lowering of the ask price increases the TOM, though the effect is very small.

Ask price relative to appraisal

The final auction-outcome variable that we consider is the sell-ask spread. As long as the sell price does not all as much in percentage term as the ask price is reduced, the sell-ask spread will increase when the ask price is lowered. Table 7 shows the net effect in the sell-ask spread of changing the ask price. Our results suggest that a lower ask price does indeed increase the sell-ask spread, which – as we will also study in more detail later – may function as a sales pitch for (some) real estate agents.

Table 6: Regressing $log(TOM)_{i,j,t}$ on $\frac{Ask_{i,j,t} - Appraisal_{i,j,t}}{Appraisal_{i,j,t}}$ .Norway, 2002-2014

	(1)	(2)	(3)	(4)	(5)
Ask dev.	-2.85***	-3.02***	-3.13***	-3.05***	-2.20***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.21)
Observations	59094	59094	59094	59094	27326
R2	0.0123	0.0219	0.0568	0.0595	0.0584
Size		✓	✓	✓	
House type FE		✓	✓	✓	
Ownership type FE		✓	✓	✓	
Building year FE		✓	✓	✓	
Zip code FE			✓	✓	✓
Time FE			✓	✓	✓
Appraisal				✓	✓
Unit FE					✓

Table 7: Regressing $\frac{Sell_{i,j,t} - Ask_{i,j,t}}{Ask_{i,j,t}}$ on $\frac{Ask_{i,j,t} - Appraisal_{i,j,t}}{Appraisal_{i,j,t}}$ .Norway, 2002-2014

	(1)	(2)	(3)	(4)	(5)
Ask dev.	-0.51***	-0.48***	-0.49***	-0.50***	-0.55***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	59253	59253	59253	59253	27425
R2	0.0604	0.0807	0.156	0.162	0.176
Size		✓	✓	✓	
House type FE		✓	✓	✓	
Ownership type FE		✓	✓	✓	
Building year FE		✓	✓	✓	
Zip code FE			✓	✓	✓
Time FE			✓	✓	✓
Appraisal				✓	✓
Unit FE					✓

4.2 Nine-ending strategies

LATE estimation of nine-ending pricing strategies

TO BE COMPLETED. PRELIMINARY RESULTS ARE CONSISTENT WITH OUR BASELINE RESULTS.

5 Mechanisms: How strategic pricing affects auction dynamics

To explore the relevance and the relative quantitative importance of the two effects that a lower ask price has on auction dynamics, we now turn to the auction data. First, we explore how a lower ask price affects the number of interested visitors on public showings. Table 8 tabulates the results. In the first column, we report results when the dependent variable is number of persons who have signed up as being interested. In the second and the third column, we distinguish between people who have signalled (to the real estate agent) that they have a substantial interest and people who have are interested, but have not signalled a substantial interest. All specifications control for numerous attributes, as well as real estate agent fixed effects. All specifications yield similar results; a lower ask price attracts more visitors to public showings.

Table 8: Ask price and interested prospective buyers at public viewings.

	Log(All interest)	Log(Big interest)	Log(Other interest)
Ask dev.	-0.85***	-0.65***	-0.53**
	(0.14)	(0.12)	(0.22)
Observations	20522	20521	5682
R2	0.587	0.773	0.423
Controls:			
Size	✓	✓	✓
House type FE	✓	✓	✓
Ownership type FE	✓	✓	✓
Building year FE	✓	✓	✓
Zip code FE	✓	✓	✓
Time FE	✓	✓	✓
Appraisal	✓	✓	✓
Realtor FE	✓	✓	✓

Having found that a lower ask price increases the number of interested prospective buyers, we explore how auction dynamics are affected. Results are reported in Table 9. Our results suggest that a lower ask price increases both the number of bidders and the number of bids, which in itself contributes to a higher sell price. However, we also find that a lower ask price curbs the opening bid of the auction. If the ask price is reduced by 1 percentage point relative to the appraisal value, we find that the opening bid is one percent lower.

Table 9: Asking price and auction dynamics.

	Log(Nr. bids)	Log(Nr. bidders)	Log(Opening Bid)
Ask dev	-0.44***	-0.66***	1.02***
	(0.14)	(0.08)	(0.02)
Observations	20523	20523	20512
R2	0.1000	0.132	0.958
Controls:			
Size	✓	✓	✓
House type FE	✓	✓	✓
Ownership type FE	✓	✓	✓
Building year FE	✓	✓	✓
Zip code FE	✓	✓	✓
Time FE	✓	✓	✓
Appraisal	✓	✓	✓
Realtor FE	✓	✓	✓

[**Incomplete section. Need to**

1. Better link the two opposing mechanisms to the net effect on the sell-appraisal spread calculated previously.
2. Can show how no. bids (appendix?) affect selling price; find that more bids leads to higher selling price
3. Show how opening bid affects sell price(appendix?); find that lower opening bid leads to lower sell price
4. Use combination of results to do calculation to net out effects and explore if it squares with previously estimated net effect
5. Alternatively plug estimates into simple model and simulate

6 Repeated transaction by real estate agents and repeat sellers

6.1 What's in it for the real estate agents?

Who are the agents offering discount?

Our results suggest that a lowering of the ask price leads to a lower sell price. Yet, more than 50 percent of the transactions are listed with an ask price that is below the appraisal value. Our results also show that a lower ask price leads to a higher sell-ask spread. This may function as a potential marketing device for real estate agents when they approach new customers and try to signal their skills. Our survey, see Fig A.1 in Appendix A, also suggest that people trust the real estate agent when deciding on the ask price. To investigate this in more detail, we start by exploring which are the real estate agents who offer a discount. For each real estate agent, we calculate:

1. The discount they have offered in each auction they have handled
2. The spread between the sell price and the appraisal value in each auction they have handled
3. The median gain across auctions

We then:

1. Draw random samples for each year (half of the sample) and calculate percentiles of gains in that sample
2. Characterize realtors as Very poor,...,Very good depending on how they perform relative to the distribution in the random sample
3. Keep only auctions from the sample that we did not use to classify the agents

Finally, to explore whether realtor quality matters for the likelihood of offering a discount, we consider the following specification:

$$P[Z_{i,t}|TimeFE, Type_{i,t}] = \frac{e^{\beta_t + \gamma' Type_{i,t}}}{1 + e^{\beta_t + \gamma' Type_{i,t}}}$$

where:

$$\begin{aligned} Z_{i,t} &= \{\text{Small discount, Large discount, No discount}\}, \\ &\text{and} \\ \text{Type}_{i,t} &= \{\text{Very poor, Poor, Normal, Good, Very Good}\} \end{aligned}$$

Marginal effects for the likelihood of offering a discount, depending on type, are summarized for the three different discount categories in Figure 9. It is clear that the poor real estate agents are more likely to offer large discounts, whereas the good agents asks for the appraisal. Thus, there seems to be a connection between realtor type and propensity to offer a discount.

Can they gain from it?

Our hypothesis is that the poor real estate agents offer a discount to improve their sell-ask spread, thereby mimicking the good agents. To explore this, we:

1. Categorize an agent as a discounting agent at time t if he offers a discount at the median (across auctions he handles)
2. Split real estate agents in two groups

Good: Agents who, at the median, achieve a sell-appraisal spread above the median

Poor: Agents who, at the median, achieve a sell-appraisal spread below the median

We then explore whether offering a discount at time $t-1$ has an impact on market shares in t. We distinguish between agents that are classified as good or poor in year $t-1$, and estimate the following equation for the two sub-groups:

$$\Delta\text{Nr. sales}_{i,t}^{k} = \alpha_i^k + \beta_t^k + \gamma^k Discount_{i,t-1}$$
$$\Delta\text{Volume}_{i,t}^{k} = \alpha_i^k + \beta_t^k + \gamma^k Discount_{i,t-1}$$

where $k = \{Good, Poor\}$. Results are summarized in Table 10. Our results suggest that the choice of strategy does not matter for the good type, but we find that the poor type gets more sales and a larger revenue by being a discounting agent. Thus, it seems optimal, conditional on being poor, to offer a discount.

Table 10: Discount strategy and future market shares.

	Poor type		Good type	
	Δ Nr. sales	Δ Volume (mill. NOK)	Δ Nr. sales	Δ Volume (mill. NOK)
Discounting agent$_{t-1}$	3.83**	17.24***	1.71	8.56
	(1.67)	(6.39)	(2.35)	(7.92)
Time FE	YES	YES	YES	YES
Real estate agent FE	YES	YES	YES	YES
Observations	613	613	677	677

6.2 Repeat sellers: Do people learn?

[TO BE COMPLETED. RESULTS SHOW THAT SELLERS WHOFAILED ON A LOW ASK STRATEGY DO NOT CONTINUE TO USE THE STRATEGY WHEREAS SELLERS THAT SUCCEEDED DOES CONTINUE TO USE THE STRATEGY]

7 Robustness and sensitivity checks

7.1 Variations over the housing cycle

SHOW AND DISCUSS FIGURES SHOWING ESTIMATED COFFICIENTS YEAR-BY-YEAR

7.2 Compositional bias

[INPUT TABLE SHOWING RESULTS FOR DIFFERENT SIZE AND PRICE CATEGORIES, AS WELL AS APARTMENTS ONLY]

7.3 Alternative measure of market valuation

WE HAVE USED APPRAISAL. AN ALTERNATIVE IS A HEDONIC PRICE. TEST ROBUSTNESS WRT THIS

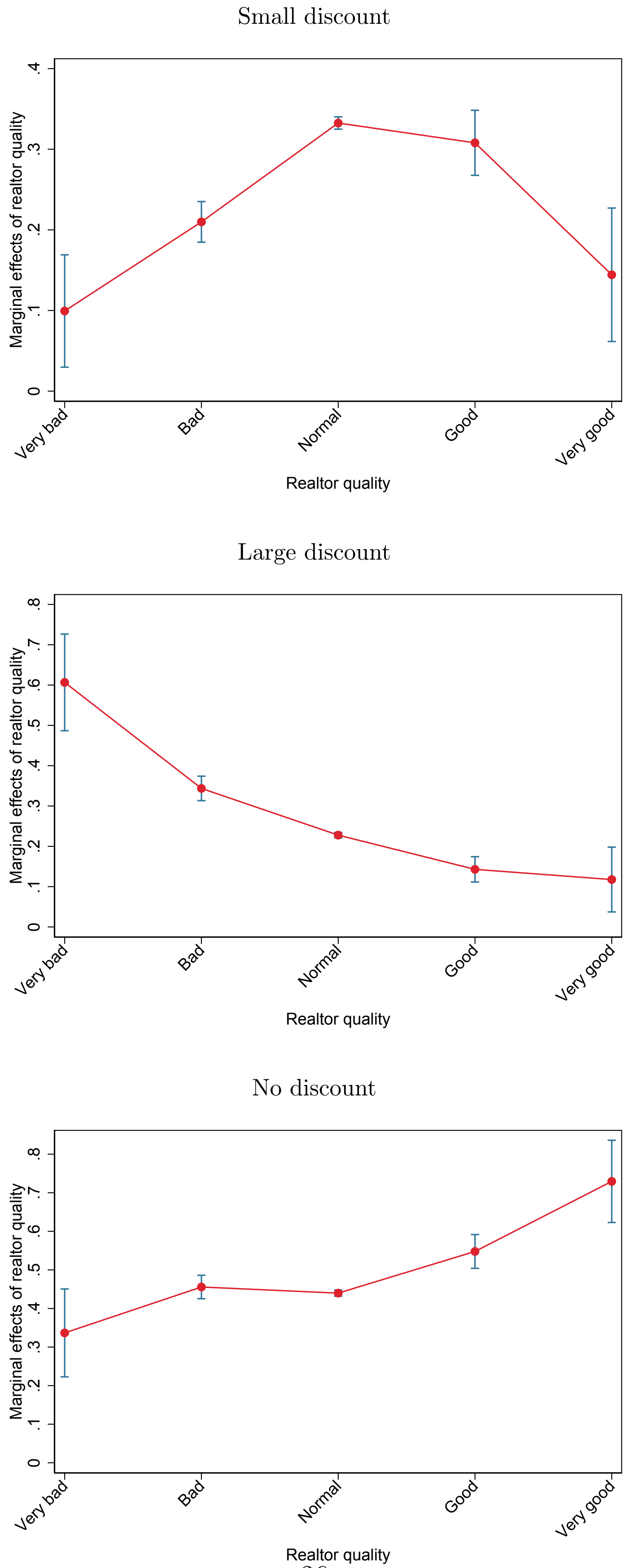
7.4 Non-linearities

TEST FOR NON-LINEARITIES FOR DIFFERENT REBATE CATEGORIES. HYBRID OF CURRENT AND PREVIOUS APPROACH.

7.5 Sensitivity to the cut-off in the LATE setup

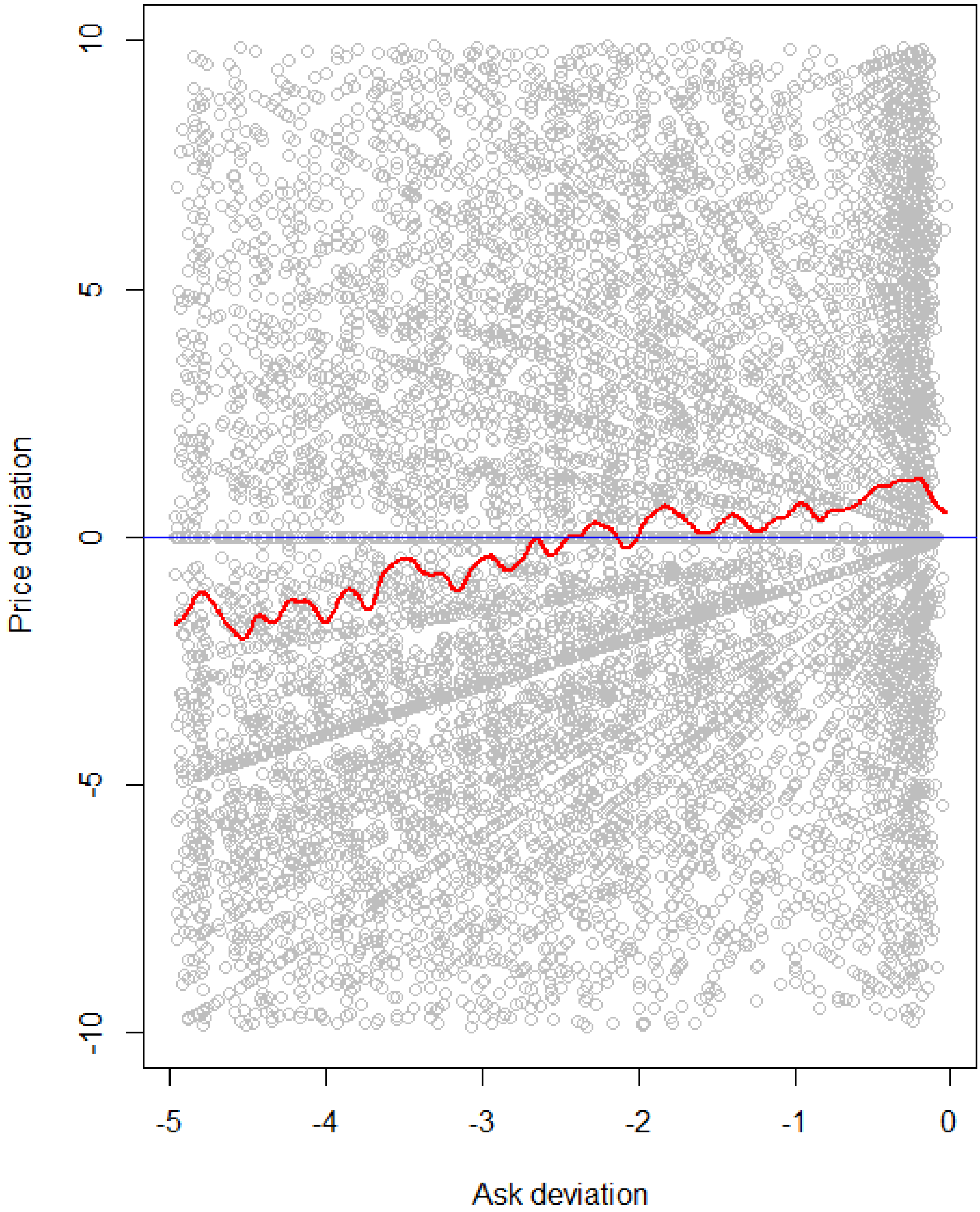
8 Conclusion

Figure 9: Realtor quality and size of discounts



Note:

Figure 10: Price deviation versus ask deviation (deviation measured from valuation)



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A Survey evidence: Why do people offer a discount?

The role of the realtor

Figure A.1: How important is the realtor in deciding the asking price?

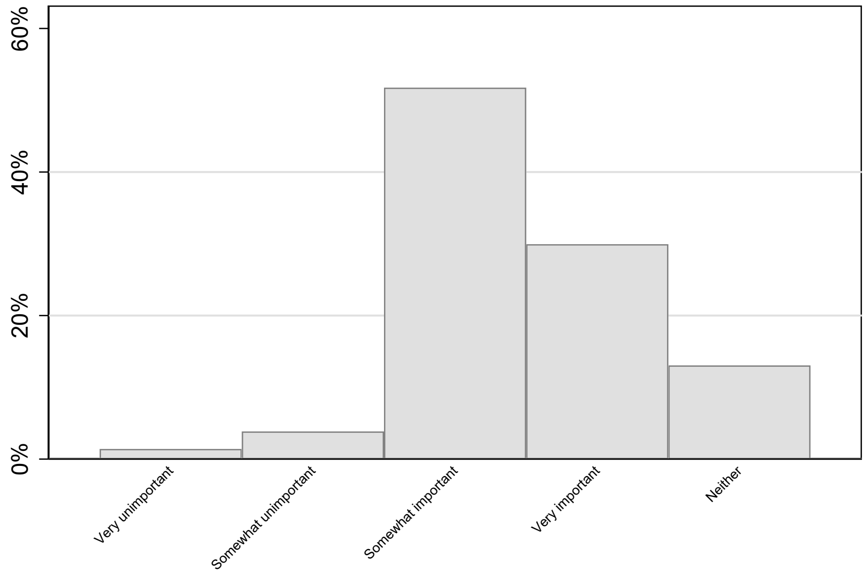
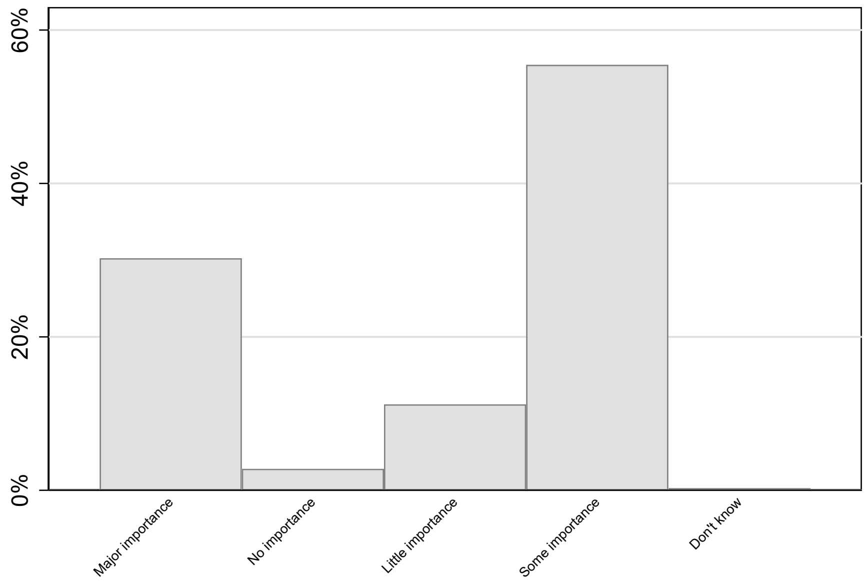


Figure A.2: How important is the realtor for the selling price?



Expectations about selling price relative to ask

Figure A.3: What do you expect regarding the selling price when you sell?

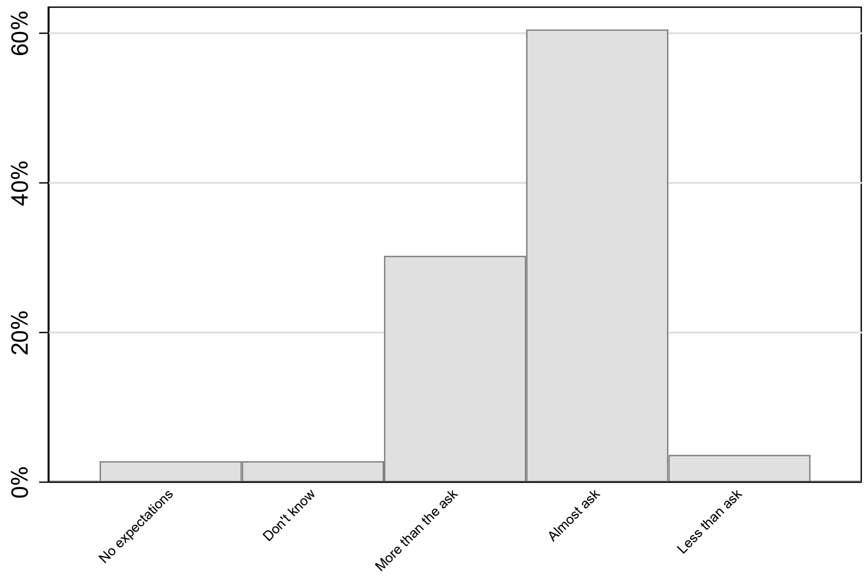
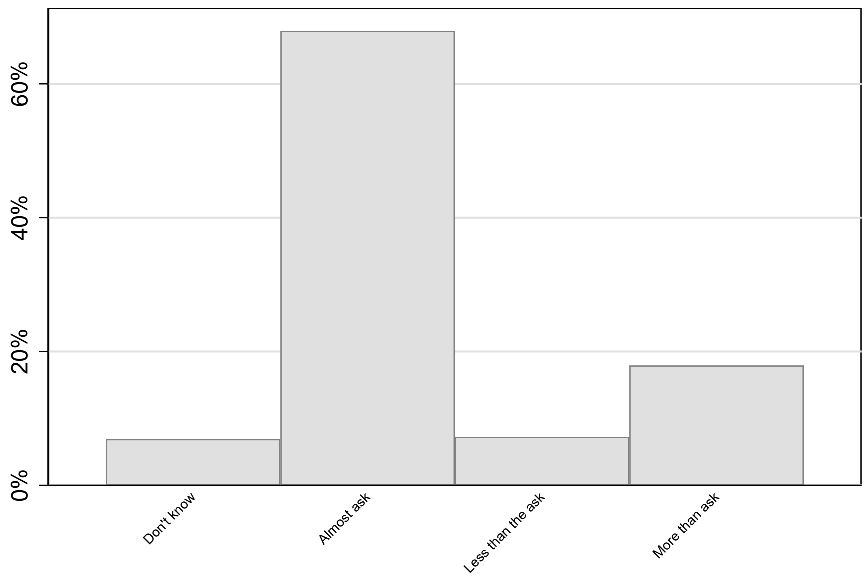


Figure A.4: What do you expect regarding the selling price when you buy?



Ask and auction dynamics

Figure A.5: Do you think a lower ask attracts more bidders?

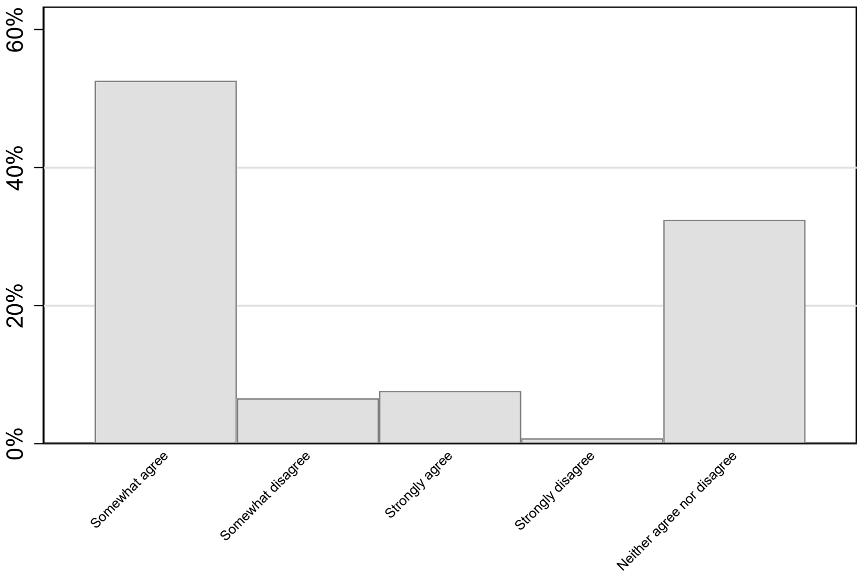


Figure A.6: The ask is the lowest price I would be willing to sell for?

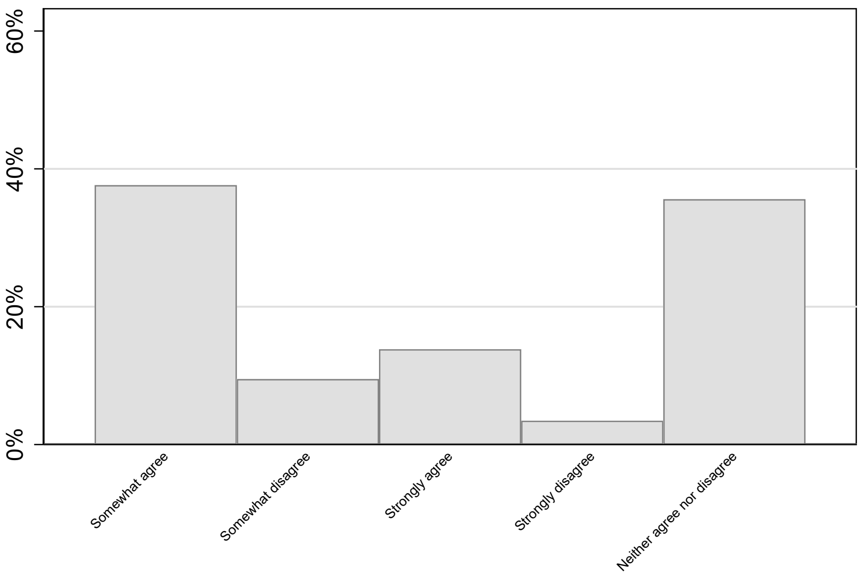


Figure A.7: Four houses are similar. You can only go to one viewing. The appraisal is 4.1 in all cases. Which viewing do you attend?

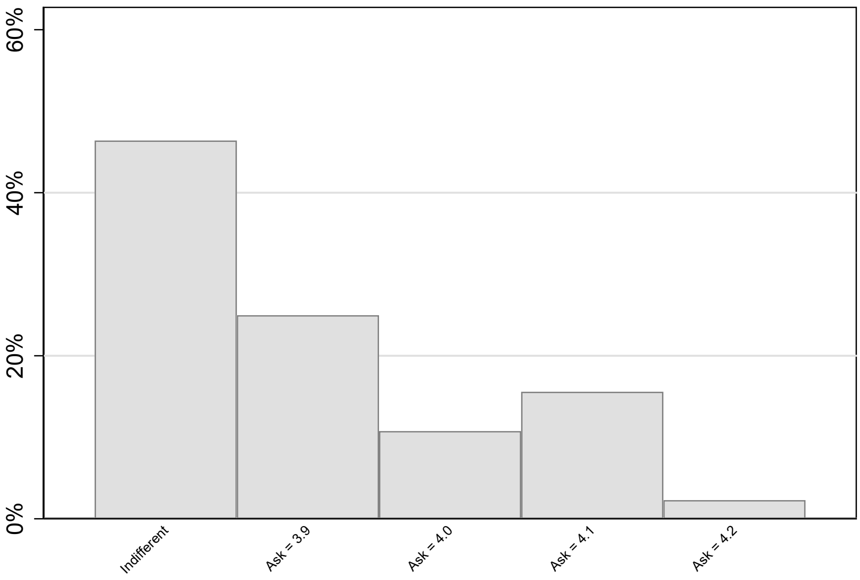
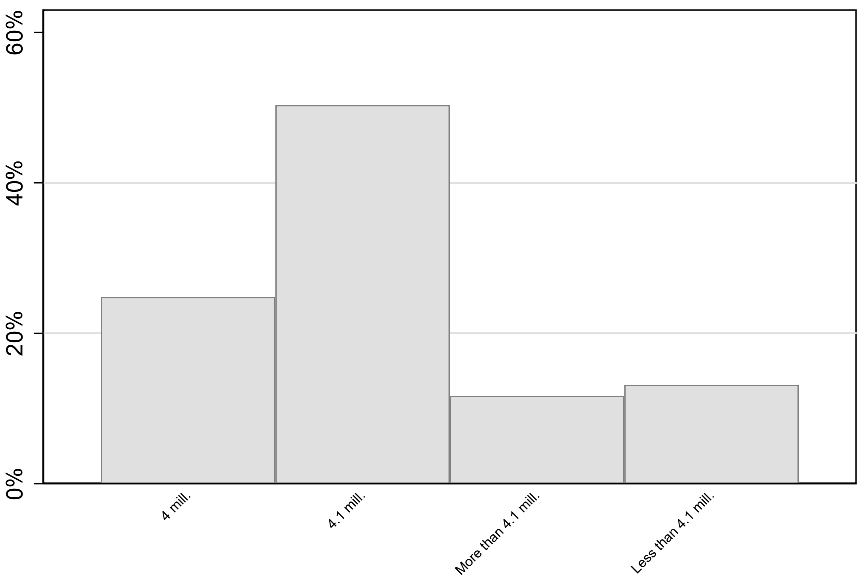


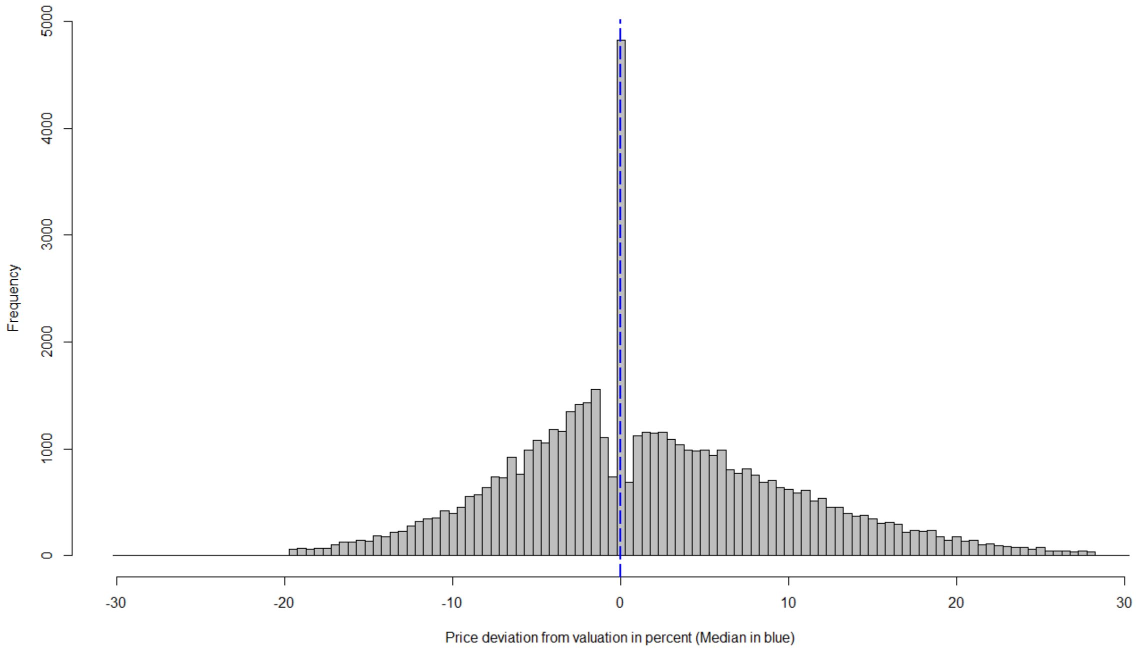
Figure A.8: Your house is valued at 4.1 million. What would you ask for?



A The valuation

Figure A.1 shows the price deviation in percent from the valuation. The median is 0 and 0 is by far the most frequent outcome. At the same time there is substantial price deviation from the valuation. This is not surprising. We may view the transaction price as a realization of stochastic variable, and the valuation at best the expected value. In other words, the best we can hope for is that the valuation is close to an unbiased estimate of market value. Figure A.1 is comforting in the sense that it is consistent with the valuation as an unbiased estimate of market value.

Figure A.1: Price deviation from valuation in percent for valuation deviations between -30.25 to 30.25 percent



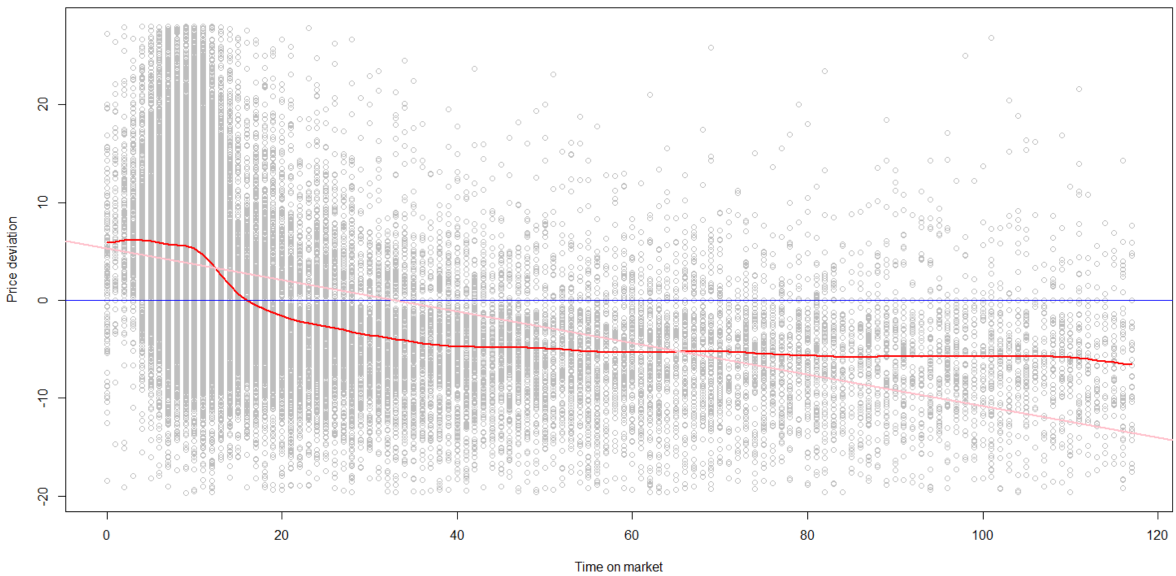
However, A.1 displays merely a crude statistics, and there may be systematic variation that is not consistent with valuation as an unbiased estimate. Time on market is a variable that is likely to affect transaction prices. Short spells are likely to correlate with higher transaction prices than expected. Or phrased differently, higher than an unbiased estimate. At the other end, long spells are likely to correlate with lower transaction prices than expected as the sellers tend to lower reservation prices over time. This latter effect is likely to be cushioned in a rising market as the valuation over time is an increasingly biased estimate of market price.

Figure A.2 shows that this is indeed the case for price deviation from the valuation. Short time on markets are associated with prices higher than evaluation and longer toms lower prices relative to the valuation. Moreover, houses with long time on market sell on average with a five percent discount. This discount remain essentially stable for toms in the range of 40 to 120 days. This flattening of the smoothed (lowess) curve, may be due to the effect of a rising market, and/or inelastic cut in reservation prices. The latter can occur if the seller has a threshold given by her mortgage.

The important thing here is whether or not the valuation may be viewed as an unbiased estimate of market price at the time when the dwelling is put on the market for agents in the housing market and for us as housing market researchers.

The brief analysis here does not reveal any serious biases. This does not rule out that their fore instance realtor fixed effects. In fact, this may be argued highly likely,as realtor assessed market prices ultimately will rely at least on the margin on personal judgment. These are of little concern unless there is a correlation say between a person driven low valuation and a the propensity for sellers to set the ask low. On the other hand, if it is likely that realtor fixed effects average out when we consider average effects (like in LATE), these effects are of little concern.

Figure A.2: Price deviation as a function of time on market (smoothed lowest curve in red. Regression line for Price deviation as a linear function of time on market in pink.



B Data preparation

C Supplementary LATE regressions and checks for balance