Price-setting and incentives in the housing market*

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Abstract

We demonstrate that in the housing market, a strategy of using a low ask price implies more interest, more bidders, and more bids, but lower opening bids. The latter effect is the strongest so a low-ask strategy decreases the spread between the sell price and the appraisal value. Yet many sellers use such a strategy. To explain this behavior, we exploit repeat-sales, repeat-bids, repeat-realtors, and repeat-sellers data sets and first construct a performance metric for realtors. Using this metric, we rank realtors and show that low-performing realtors more often than high-performing realtors are associated with a low-ask strategy. Among low-performing realtors, however, there is an association between a higher frequency of low-ask strategies this year and higher revenues next year. In contrast, there is no such association among high-performing realtors. Sellers learn, albeit modestly. A seller who previously used a low-ask strategy but obtained a sell price below appraisal value tends to employ the strategy less frequently.

Keywords: *Auction dynamics; Housing market; Principal-agent problems; Signalling; Strategic pricing*

JEL classification: *D14; D44; D90; R21; R31*

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1 Introduction

Selling is an activity economists take an interest in studying. Yet, many aspects of the selling-process are not fully understood. One example can be found in the Norwegian housing market, in which half of the sellers set an ask price below an estimated market price. We believe this strategy separation begs an explanation. If a lower ask price is optimal, then everyone would do it. If it is not, then nobody should do it. This article asks two related questions: How does setting a low ask price affect the sell price? Why do people choose different strategies in setting the ask price?

In answering these questions, we study ask prices and sell prices in housing transactions and the behavior and incentives of sellers, bidders, and realtors in the housing market. We follow agents over time and trace how their decisions have consequences for auction dynamics and outcomes. This means that our study involves both principal-agent problems (Ross, 1973; Jensen and Meckling, 1976; Mirrlees, 1976; Lazear, 2018; Kadan et al., 2017) and signalling (Akerlof, 1970; Spence, 1973, 2002). The principal-agent problem arises because the realtor and the seller do not necessarily have aligned incentives. The signalling structure emerges since there is a competition on message among sellers over prospective buyers. After all, the most powerful signal is the ask price. Set it too high and you scare away buyers. Set it too low and you tell the buyers that the unit is unattractive, or signal that you are in a desperate financial situation.

With the advent of online advertising and digital auctions, 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. In this digital environment, setting the ask price at the correct level is more important than ever. To get it right, the seller consults a realtor, which in turn involves a screening problem, namely to find the right realtor. The seller looks for observable evidence of skills and effort in order to screen (Stiglitz, 1975; Riley, 2001) realtors. One metric that helps the seller in this regard is the realtor's track-record on the percentage difference between the sell price and the ask price. Knowing that sellers observe sell-ask spreads, and use them when screening, the realtor takes this into account when advising the client and she contemplates the impact such spreads have on the recruitment of future clients.

While the contribution of this paper is empirical, we start by developing a skeleton model outlining how sellers face a trade-off between a herding (Banerjee, 1992) and an anchoring (Tversky and Kahneman, 1974) effect when setting the ask price. The herding effect entails that a lower ask price generates more bidders, which contributes to a higher sell price. The anchoring effect arises because a lower ask price anchors the opening bid in the auction, which has a negative effect on the final bid.

We use an appraisal value to estimate the market price of a house. The appraisal value is set by an independent and government-approved appraiser, who physically inspects the home, writes a technical report on the condition of the house, and estimates its market price. We explore how an ask price lower than the appraisal value affects number of bidders, the opening bid, and the sell price. To control for unobserved heterogeneity, we follow units that are sold at least twice and include unit-fixed effects in our regressions. Regressions also include year-by-month, realtor, and realtor-office fixed effects. Our results show that the anchoring effect is considerable. In fact, an ask price five percent below the appraisal value tends to result in a sell price four percent below the counterfactual sell price that would have been achieved without lowering the ask price. We also document a herding effect, but this effect is dominated by the anchoring effect. The end result is that a lower ask price results in a lower sell price.

To understand why so many sellers set lower ask prices when they do not result in higher sell prices, we study the principal-agent problem arising from differences in incentives between sellers and realtors. Sellers want a high sell price, and they typically hire a realtor to help sell their house. In a motivating model, we show that realtors face an inter-temporal trade-off between current and future profits. Current sell-ask spreads are used to attract future customers. Since a reduction in the ask price reduces the sell price, but not fully, a reduction in the ask price increases the sell-ask spread, leading to an increase in future profits. However, since a lower ask price contributes to a lower sell price, current profits are reduced. Empirically, we investigate whether it is optimal for the realtor to advise a high or low ask price and whether it depends on the realtor's skills.

Specifically, we classify realtors into skill-groups based on their achieved sell-appraisal spreads. We observe that superior realtors tend not to be involved in transactions in which strategically low ask prices have been used. Lesser skilled realtors, however, tend to be associated with such transactions. Moreover, a time-series regression among lesser skilled realtors shows that when a realtor in one year tends to use strategic ask prices, this realtor sees more business the next year. For superior realtors, there is no such association.

Our final investigation involves a study of repeat-sellers. We follow sellers across multiple sales, and look at how sellers have used low-ask strategies, not used such strategies, or both in the past. Results indicate that when all previous sales using a low ask price were associated with a sell price above the appraisal value, the seller was more likely to use a low ask price subsequently compared to situations when this is not the case.

Our analyses are based on a unique combination of Norwegian data on repeat-sales, repeat-bids, repeat-realtors, and repeat-sellers. Our main data set contains a complete log of all bids in all auctions, including unit, bidder and realtor identifiers across auctions, from DNB Eiendom – one of the largest realtor companies in Norway. The data include more than half a million bids during the period 2007-2015. The data set includes information on every single bid, including time when the bid is placed (precise down to the minute), expiration of the bid (precise down to the minute), unit-identifier, bidder-identifier, realtor-identifier, realtor-office-identifier, ask price, appraisal value, and numerous attributes of the unit being sold. These data allow us to follow repeat sales of the same housing unit, as well as the performance of individual realtors across auctions. To study learning among sellers, we examine a second data set. It is collected from official registry information on buyers and sellers in Norway and is a complete list of properties and owners. Finally, we attached questions to an omnibus survey of households undertaken by Norway's largest bank, DNB. The main reason for collecting these data is to understand how buyers and sellers think about the role of the ask price in housing auctions, as well as their perceptions about the importance of the realtor in the selling process.

The contribution of this paper is two-fold. First, we bring a unique data set on bidding-activity in the housing market to questions on price-setting and incentives, which has bearing on results in the signalling and agency literature. Second, we explore in detail to which extent general results on signalling and principal-agent problems hold in a large-stake market such as the market for residential real estate. The questions on signalling and agency are: i) Does signalling through a strategically low ask price increase the sell price?, ii) Which type of realtors advise the use of strategic ask prices? iii) Why do such realtors give such advise? iv) Do sellers learn? Evidence suggests that the answers are: i) No, ii) Low-skilled realtors, iii) To maximize individual pay-off, iv) Yes, to some extent.

Our analysis is confined to the Norwegian housing market. There are two main reasons for this. First, Norway is, as far as we know, the only country in the world in which detailed registry data on the bidding-process have been systematically collected for a reasonably long time-period. Furthermore, the institutional setting of the Norwegian housing market makes it well-suited for studying the effect of strategic ask prices since transactions are set up as classic ascending bid auctions. A typical transaction follows a procedure that makes ex post inspection easy. A seller advertises a unit for sale online, which leaves an electronic trace of advertising date, ask price, and appraisal value. In the advertisement, the seller announces a date for a public showing (open house). Interested parties inspect the unit on this showing. All bids are legally binding. The acceptance of a bid is legally binding. The bidding activity takes place on digital platforms, and are quick and transparent.

We explore the robustness of our findings along several dimensions. First, as an alternative to using the appraisal value to represent the ex ante market price, we estimate a hedonic model to gauge the market price of all units in the data set. Results are robust to this change of approach. Second, we explore if results are robust to segmentation on size, price and location. They are. Data at the transaction level are available for all sales handled by all real-estate agencies in Norway through the firm Eiendomsverdi. In contrast to our main data, these data do not include information on within-auction dynamics, but we show that the result that a lower ask results in a lower sell price is maintained in this larger data set. Third, we test for possible time-variation by redoing our analysis on a year-by-year basis. Potential non-linear effects of lowering the ask could arise if larger adjustments of the ask price are driving the results. Our results are robust to both changes. To explore whether lowering the ask works for certain nominal price levels, we redo our analyses across the nominal price spectrum. None of our results are materially affected. Finally, we show that an instrumental variable approach that takes care of potential self-selection by, and unobserved heterogeneity among, sellers yield similar results as our baseline approach.

Our paper contributes to several streams of the literature. First, how to optimally set ask prices is the central question in one stream. It is likely that sellers start out by contemplating their reservation price, but that their ask price is not identical to it (Horowitz, 1992; Taylor, 1999). Ask prices may also be linked to demand uncertainty (Herrin et al., 2004) and the strength of the market (Haurin et al., 2013). 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 sales probability. Our paper contributes to this literature by showing that sellers in the housing market choose different strategies, and that they are motivated to cut the ask price to attract more bidders. However, their behavior indicates that they do not fully appreciate the strength of the anchoring effect compared to the herding effect. This is understandable given the infrequency of a seller's home-selling. A seller simply has little experience in selling his house. We show, however, that sellers learn, albeit modestly, as their selling experience grows.

Another stream followed the seminal study on anchoring by Tversky and Kahneman (1974), and anchoring effects have since been documented in art auctions (Beggs and Graddy, 2009), DVD auctions on eBay (Simonsohn and Ariely, 2008), and in the housing market (Northcraft and Neale, 1987; Bucchianeri and Minson, 2013). Theoretically, Merlo et al. (2015) suggests that sellers set the ask price to anchor subsequent negotiations. That nominal prices have an impact on decision-making in the housing market has also been shown in the important study on loss aversion by Genesove and Mayer (2001). Our paper contributes to this literature by showing that lowering the ask price curbs the opening-bid in housing auctions, which again lowers the sell price, suggests that anchoring effects are present in ascending bid auctions in a large-stake market.

We also contribute to the literature on bidding-behavior and herding. Ku et al. (2006) argues that a lower ask price can generate more bids and a higher sell price. Using eBay data, Einav et al. (2015) find mixed evidence for this. In the housing market, Han and Strange (2016) and Repetto and Solis (2019) show that lowering the ask price leads to an increase in the number of bids. Our results corroborate this finding by documenting that a lower ask price results in more bids. However, our results nuances these findings, since we find a relatively marginal effect of lowering the ask on bidding activity relative to the negative effect a lower ask price has on the opening-bid. The end result is that a lower ask leads to a lower sell price.

In eBay-auctions, it has been documented that round number asks send a signal of weak bargaining power, resulting in lower sell prices (Backus et al., 2019). Related to this, Beracha and Seiler (2014) find that the most effective pricing strategy for a seller in the housing market is to use an ask price that is just below a round number. Supporting evidence is found in Repetto and Solis (2019). Our paper studies the effects from a more general strategy of setting the ask price lower than an ex ante estimate of the market value.

Rutherford et al. (2005) find that houses owned and sold by a real-estate agent sell at a price premium. Similar results have been established in Levitt and Syverson (2008). Agarwal et al. (2019) show that real estate agents, when they buy themselves, are able to purchase at a lower price. Barwick et al. (2017) find that lower commission fees result in lower sale rates and slower sales. This paper contributes to the literature on agency since mis-aligned incentives between a principal (realtor) and an agent (seller) arises when the realtor seeks to maximize current and future profits, while the seller wants to maximize a single sell price. In particular, we show that even though a lower ask price is sub-optimal, low-skilled realtors rationally advise sellers to cut the ask price in order to expand their customer base and profits in the near future.

The outline of the paper is this. In the next section, we describe the institutional setting of the Norwegian housing market and outline a skeleton model of the trade-offs faced by a seller when setting the ask price. In Section 3, we present our data. Results on the effects of strategic ask prices on auction dynamics and outcomes are presented in Section 4. A motivating model for realtors' incentives when advising on ask prices is presented in Section 5. In the same section, we show that there are differences in the propensity to offer a discount and the effect of this strategy on future profits across realtor types. We also show what sellers learn as they gain more experience. Sensitivity and robustness checks are discussed in Section 6. The final section concludes and discusses some policy implications of our results.

2 Institutional details and a skeleton model

2.1 Institutional setting

Realtors

Most sales of houses and apartments in Norway are brokered by a realtor[1], who is hired by the seller. In contrast to the US and many other countries, the buyer does not hire a separate realtor in Norway. According to Norwegian law, the realtor is required to take care of the interest of both the seller and the buyer, and he is obliged to give advice to both seller and buyer on issues that may impact the selling process.

There exists a code of regulation that governs who can work as a realtor and use the title. In particular, mediating housing sales requires that the realtor's firm has obtained a permission from the Financial Supervisory Authority. In certain cases, a sale can also be managed by lawyers, but it is customary that sellers hire realtors. Becoming a realtor requires obtaining a license, which is achieved after having completed a 3-year bachelor's degree. In addition to the license, 2 years of practical experience is required for an agent to be allowed to assume the main responsibility of brokering a housing sale.

According to registries maintained by the Financial Supervisory authority, there are 4,232 licensed and 1,484 active realtors in Norway, and a total of 504 firms. These firms maintain over 1,118 local branches that are involved in real estate brokerage, out of which 164 belong to the DNB Eiendom system. A realtor's compensation scheme typically includes a variable fee, which is proportional to the sales price.

Appraisers

Until 2016, a person who decided to sell her property, typically obtained an appraisal value from an appraiser.[2] The appraiser[3] would inspect the home prior to the advertisement and write a technical report about the general condition of the unit. The report would include a description of the material standard, technical issues, and other information. For example, the appraiser would identify a need

[1]Over the past 2-3 years, it has been a modest, but growing tendency that sellers mediate the sale themselves. Our sample is confined to the period 2007–2015, during which period self-brokered sales rarely happened.

[2]From 2016 onwards, the value estimate is made by the realtor.

[3]In Norway, many professional titles are protected by law, e.g. lawyer, physician, or psychologist. It is illegal for non-licensed practitioners to use these titles. However, "appraiser" is not a legally protected title even if there exists education aimed at training appraisers. A typical background for an appraiser lies in engineering, thus some appraisers use the term "appraisal engineer".

for drainage, measures of water pressure, and potential problems with moisture.[4] The report would describe the age of bathrooms and washing rooms and include detailed information about 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 price. 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 value and the technical report were common knowledge to buyers.[5]

The selling process

In Figure 1, we summarize the selling process in Norway. Having collected an estimate of the market price, the seller makes a decision – in collaboration with the realtor – on the asking price. The seller may choose to set an ask price that is lower than, equal to, or higher than the estimated market price. The ask price is a signal and the seller is not obliged to accept a bid at, or even above, it. The seller may therefore choose the ask price strategically in an attempt to affect the outcome of the auction. The realtor needs to explain thoroughly to the seller the difference between the estimate of the market value of the unit and the reservation price of the seller because declining bids at the ask price may imply scrutiny of the agency. [6]

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. Most units are announced for sale on Fridays.[7] In the advertisement, the seller states when there will be a public showing of the unit, which in the capital Oslo typically happens on a weekend seven or eight days after posting the advertisement. The auction commences on the first workday that follows the last public showing, but it is possible, and legal, to extend bids prior to the public showing. Since most units are listed on Fridays, there will be fierce competition among sellers to attract people to their public showing. This is the invitation for strategically setting a low ask price in competition with other sellers to attract more people to visit the public showing and inspect your house.

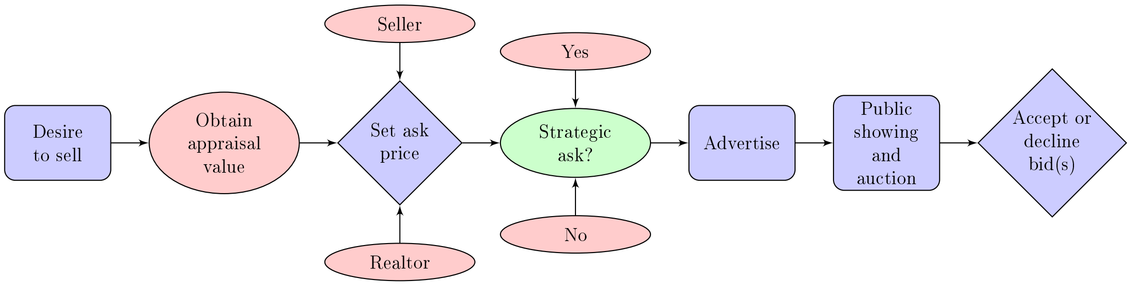
[4]For more information, see norsktakst.no or nito.no/english for online descriptions of Norwegian appraisers.

[5]After 2016, the appraiser may still be hired to write a report, but the realtor is responsible for estimating the market value of the house.

[6]The recommendations for real estate agencies contain passages aimed at reducing the frequency of instances in which bids above the posted ask price are declined. The wording, although vague, includes possible sanctions towards agencies that are shown systematically to be involved in such transactions.

[7]See Figure Figure B.1 in Appendix B.

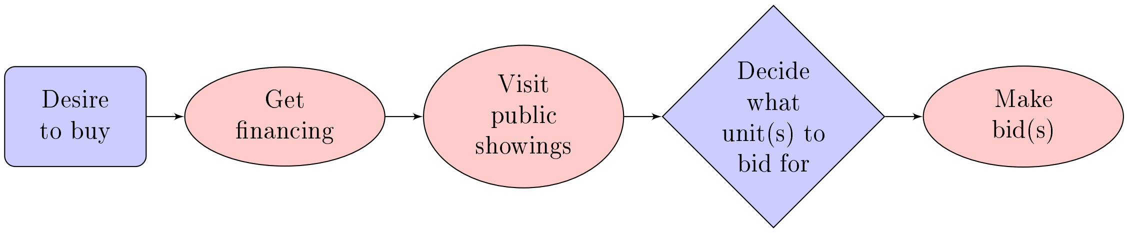
Figure 1: The selling process



The buying process

In Figure 2, we summarize the process of buying. A buyer first consults with his bank to collect proof of financing. The buyer documents his and his household income, debts and assets, and his status as married, single, or living with a partner. The bank assesses the financial ability of the applicant.[8] Conditional on financing, the search process begins. Note that the proof of financing is not contingent on buying a particular unit – it reflects the maximum bid the buyer can announce in any auction of any house. 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 buyer visits units of interest that are 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.[9]

Figure 2: The buying process



[8]Starting in 2017, mortgage loans became regulated. The regulation includes a passage stating an LTV-limit of 85% and a maximum (total) debt-to-income ratio of 5. In addition, banks need to comply with legal requirements.

[9]It is legal, and common, to make conditional bids. Usually, the conditions involve an expiration time, e.g. 30 minutes or noon the next day, but conditions may also include statement about access to financing. Most bids have an expiration time less than one hour.

The auction

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

2.2 A skeleton model for setting the ask price

Consider a housing market with N_B buyers and N_S sellers. Houses are both vertically and horizontally differentiated.[10] For a given house h, a buyer b has a latent match quality, $M_{h,b}$ between his preferences, F_b, the vertically differentiated attributes of the house, AT_h, and the horizontally differentiated qualities of the house, Q_h, such that $M_{h,b} = m_h(F_b, AT_h, Q_h)$. The matching function m_h is continuous and differentiable. Thus, for each house indexed $h = 1, ..., N_S$, there exists a latent match quality vector, $\mathbf{M}_h = \{M_{h,1}(F_1, AT_h, Q_h), ..., M_{h,N_B}(F_{N_B}, AT_h, Q_h)\}$ between house h and buyers $b = 1, ..., N_B$. Buyer b can estimate this latent match quality when he sees the advertisement containing information about the vertically differentiated attributes, AT_h and description of some of the horizontally differentiated qualities Q_h (e.g. location, color, build year). The estimated latent match quality for buyer b of house h is denoted $\tilde{M}_{h,b}(AT_h, Q_h)$.

Buyer b searches across all N_S houses in the online advertisement platform, but cannot visit the public showing (open house) of all N_S. He makes a decision to visit the public showing of the k houses with highest estimated latent match quality. Let $D_{h,b} = 1$ if buyer b decides that house h is within the group of these k houses and visits the public showing of house h. It is zero otherwise. $D_{h,b} = 1$ if:

$$D_{h,b} = \begin{cases} 1, & g(\tilde{M}_{b,h}, I_b) \geq \phi(A_h) \\ 0, & \text{otherwise,} \end{cases} \tag{1}$$

[10] We define vertical differentiation as differentiation in which there exists an observable attribute along which everyone agrees on the ranking. For example, larger is preferable to smaller. We take horizontal differentiation to mean differentiation in which there does not exist a quality over which individual tastes matter and there is no agreement.

in which I_b is short notation of buyer b's income, equity, and financial position. A buyer only visits a house h if he feels his estimated match-quality based on attributes A_T combined with his financial position justifies it. There exists a threshold at which, a marginally higher ask price A_T changes $D_{h,b}$ from 1 to 0. We let an unspecified function ϕ represent this feature. For buyer b the number of 1's is capped at the upper limit k, i.e. $\sum_{i=1}^{N_S} D_{h,b} \leq k$. The buyer visits the k houses with highest $g(\tilde{M}_{b,h}, I_b)$, in which both estimated match-utility and financial position are taken into account.

All buyers make a decision on whether or not to visit the public showing of house h and we let V be a latent counting function that counts the number of visitors as a function of the ask price:

$$V_h(A_h) = \sum_{b=1}^{N_B} D_{h,b}), \tag{2}$$

in which for short notation the threshold $\phi(A_h)$ is suppressed from the decision function. The ask price A_h is chosen by the seller and exogenous to buyer b, but matters in buyer b's decision to visit or not. Thus, the ask price A_h is a variable that affects the latent counting function of visitors to house h V_h, but the seller of house h cannot ex ante know the shape of this latent function. In order to understand the relationship $V_h(A_h)$, the seller of house h consults with his realtor. Ex post, the number of visitors becomes observable to all participants.

The latent match-quality $M_{h,b} = m_h(F_b, AT_h, Q_h)$ between house h and buyer b is revealed upon inspection of horizontally differentiated qualities, Q_h. Buyer b uses his revealed match-quality to form his private value of house h, $PV_{b,h}$, and he estimates the common value $\tilde{CV}$ based on the ask price A_h, and the number of visitors to the public showing (open house) of house h, $V_h(A_h)$.

Combining the private value and the common value with his income, equity, and financial position, I_b, buyer b forms his willingness to pay for house h. The willingness to pay for house h, WTP_h, results from a utility-optimization program over the utility extracted from the service stream from the house h and other goods with the constraints on the budget from his financial position:

$$\begin{aligned} WTP_{h,b} &= \omega_b(PV_{h,b}(M_{h,b}), \tilde{CV}_{h,b}(A_h, V_h), I_b) \\ &= \omega_b(PV_{h,b}, \tilde{CV}_{h,b}(A_h, V_h(A_h)), I_b))), \end{aligned} \tag{3}$$

in which we have suppressed the determinants for the private value in order to emphasize the dependency on ask price. In buyer b's willingness to pay for house

h, the ask price enters two times, directly in his estimate of the common value and indirectly through the counting function of number of visitors to the public showing. To highlight this feature, using as short notation as possible, we write:

$$\tilde{CV} = \tilde{CV}(A, V(A)). \tag{4}$$

The total derivative of WTP with respect to the ask price is given by:

$$\frac{dWTP}{dA} = \frac{\partial WTP}{\partial \tilde{CV}}\left(\frac{\partial \tilde{CV}}{\partial A} + \frac{\partial \tilde{CV}}{\partial V}\frac{\partial V}{\partial A}\right) \tag{5}$$

The total derivative of the willingness to pay with respect to the ask price contains two terms. The first, $\frac{\partial WTP}{\partial \tilde{CV}}\frac{\partial \tilde{CV}}{\partial A}$, is the *direct* effect on the estimated common value of an ask price change. It has two factors. The first factor of the first term, $\frac{\partial WTP}{\partial \tilde{CV}}$, is positive. When the estimated common value increases, so does the willingness-to-pay. The second factor of the first term, $\frac{\partial \tilde{CV}}{\partial A}$, is also positive since the buyer knows that the seller is the most knowledgeable source of the value of the house.

The second term has three factors. It shares the first factor with the first term. The second factor, $\frac{\partial \tilde{CV}}{\partial V}$, is positive since a higher number of visitors signals higher buyer interest. The third factor, $\frac{\partial V}{\partial A}$, however, is negative since higher ask price increases the threshold, $\phi(A)$, in the decision to visit the public showing.

The first term is the *the anchoring effect* and the second term is the *herding effect*. Their relative importance will determine the change in ask price on the change in the willingness-to-pay.[11]

3 Data and descriptive statistics

Auction data

We have obtained detailed bidding 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 detailed information on every bid placed

[11] To shed light on the relevance of these mechanisms, we explore how the sell-appraisal spread relates to number of bidders and the nominal level of the opening bid in auctions. We control for common debt, appraisal value, realtor fixed effects, realtor office fixed effects, and year-by-month fixed effects. We consider a sample of units transacted at least twice, so that we can control for unobserved heterogeneity using unit fixed effects. Results are summarized in Table B.1 in Appendix B. More bidders increase the sell price relative to the appraisal value. Thus, to the extent that the ask price impacts the number of bidders, it will contribute to a higher sell price. On the other hand, a higher opening bid is associated with a lower sell price. Therefore, if a lower ask price curbs the opening bid, it will anchor the entire auction and lead to a lower selling price.

in every 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 time at which the bid was placed (with precision down to the minute), and the expiration of the bid (with precision down to the minute). Additionally, the data set contains information on the ask price, appraisal value, attributes of the unit, and the number of visitors to people the public showing. Since the appraisal value ceases to be obtained in 2016, we confine our analysis to the period 2007-2015.

We extract information on each transaction, including time-on-market, the spread between the sell price and the appraisal value, and the spread between the sell price and the ask price. We employ measures of auction-activity such as the number of bidders and the spreads between the opening bid and the ask price, the appraisal value, and the final sell price. Table 1 summarizes the data. We segment the data in two groups: Sales that have an ask price below the appraisal value and sales with an ask price greater than or equal to the appraisal value.

About half of the transactions have an ask price below the appraisal value. On average, an auction has about seven interested parties, and a bit more than two bidders. This holds true regardless of whether the ask is below or above the appraisal value. The opening bid is typically lower than the ask price and the appraisal value for both segments. However, for units with a low ask price, the distance between the opening bid and the appraisal value is larger, indicating that there may be an anchoring effect associated with this strategy. This is supported by looking at the distance between the opening bid and the ask price, which is similar across the two segments. Auctions with units listed with a lower ask price results in a sell price that, on average, is below the appraisal value. In contrast, units with an ask price greater than or equal to the appraisal value have a positive sell-appraisal spread.

In general, units with a low ask price are smaller and cheaper, and apartments are represented more often than detached houses. Setting a low ask price is more often observed in the capital city of Oslo. To explore the sensitivity of our results to the heterogeneity in type and geography, we employ robustness tests to estimation by partitioning data using type (detached houses and apartments), size (small and large), and price. In addition, we test the robustness of our results to estimation on a non-Oslo segment.

Realtor data

The data from DNB Eiendom contain a unique realtor identification-variable for the agent who manages the auction. This identification-variable is consistent across auctions and over time. Since we are also interested in studying what characterizes the agents who are associated with auctions involving units with low ask prices and how it affects their future sales, we construct a separate realtor data set. In

Table 1: Summary statistics for auction level data, segments of the ask price-appraisal value differential

	Ask price $<$ Appraisal value		Ask price $\geq$ Appraisal value	
Variable	Mean	Std.	Mean	Std.
Sell (thou. USD)	428.76	197.62	415.69	212.82
Ask (thou. USD)	417.99	195.04	405.05	206.21
Appraisal (thou. USD)	433.47	201.78	403.99	205.99
Square footage	1056.89	527.05	1126.66	518.53
Discount (in %)	3.59	4	-.34	4.76
Sell-Appraisal (in %)	-.68	9.52	3.11	9.56
Sell-Ask (in %)	2.97	8.35	2.79	8.69
TOM	36.3	37.42	27.69	26.74
No. bidders	2.41	1.7	2.25	1.5
No. interested	7.34	8.81	7.2	8.5
Opening bid-ask (in %)	-6.78	6.45	-7.02	6.59
Opening bid-appraisal (in %)	-10.1	7.49	-6.72	7.65
Opening bid-sell (in %)	-9.16	7.2	-9.21	7.35
Perc. owner-occupied	64.76		71.61	
Perc. apartment	59.53		49.29	
Perc. Oslo	32.52		21.27	
No. auctions	33,917		39,362	
No. bids	245,592		267,290	

Notes: The table shows summary statistics for auction level data over the period 2007–2015. We distinguish between units with an ask price lower than the appraisal value and units with an ask price greater than, or equal to, the appraisal value. For each of the segments, the table shows the mean, median and standard deviation (Std.) of a selection of key variables. NOK values are converted to USD using the average exchange rate between USD and NOK over the period 2007–2015, in which $USD/NOK = 0.1639$

Table 2, we compare key variables for realtors who are associated with auctions involving units with low ask prices to other realtors. Realtors who are associated with auctions involving units with a low ask price are defined as those realtors who are associated with auctions involving units with ask prices below the appraisal at least as many times as the median realtor in their municipality. Summary statistics are reported in Table 2. The sell-appraisal spread is somewhat lower for realtors who are associated with auctions involving units with ask prices. These realtors are associated with fewer sales per year and have a lower revenue per year. They appear, however, to be active for as many years as the realtors who are not associated with auctions involving units with ask prices.

Table 2: Summary statistics for realtor data, discounting versus non-discounting agents.

	Low-ask realtors		Non-low-ask realtors	
Variable	Mean	Std.	Mean	Std.
Sell-appraisal (in %)	1.28	18.29	1.92	55.9
No. sales	29.96	18.19	31.66	18.43
Revenue (mill. USD)	12.68	9.05	13.45	9.63
No. years active	5.4	1.75	5.46	1.82
No. realtors	351		307	
No. obs.	41844		38411	
No. realtors	351		307	
No. obs.	41,844		38,411	

Notes: The table shows summary statistics for the realtor-level data over the period 2007–2015. We distinguish between realtors that we characterize as "Low-ask realtors" (offering a low ask 50% more frequently than their colleagues in the municipality) and "Non-low-ask realtors". For each of the sub-samples, the table shows the mean, median and standard deviation (Std.) of some key variables.

Repeat-seller data

We accessed transaction and owner databases of the private firm Eiendomsverdi AS over the period 1 January 2003 – 28 February 2018. Eiendomsverdi AS collects 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, 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.

We require that a realtor has been involved in the sale and that both ask price and appraisal value exist. Each unit owner is uniquely identified, but multiple owners are possible. We retained owners with owner-shares of 1/1, 1/2, 1/3, 2/3, 1/4, and 3/4. There were 633,603 observations that satisfied our conditions, out of which 530,430 were unique individuals and 67,746 individuals were observed to buy exactly twice.

Survey data

To better understand how people perceive the role of the asking price, we surveyed 2,500 customers of the largest Norwegian bank, DNB. Our questions were included in a larger survey on the housing market 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 for our purpose; namely people's expectations about selling and purchase prices relative to the ask 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 ask 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.

4 How strategic pricing affects auction dynamics and auction outcomes

4.1 Empirical specification

We study how a low ask price affects auction dynamics and auction outcomes. Our variables of interest, y, are given by:

$$y_{i,j,t} = \Bigg\{ No.Viewers_{i,j,t}, No.Bidders_{i,j,t}, \frac{Opening\ bid_{i,j,t} - Appraisal_{i,j,t}}{Appraisal_{i,j,t}}, \frac{Sell_{i,j,t} - Appraisal_{i,j,t}}{Appraisal_{i,j,t}}, \frac{Ask_{i,j,t} - Appraisal_{i,j,t}}{Appraisal_{i,j,t}} \Bigg\}$$

The empirical specification used to test how a lower ask price-decision impacts these variables is given by:

$$y_{i,t} = \eta_i + \alpha_t + \zeta log(\hat{P})_{i,t} + \beta \frac{-\left(Ask_{i,t} - Appraisal_{i,t}\right)}{Appraisal_{i,t}} + \varepsilon_{i,t} \quad (6)$$

in which i indexes the unit that is sold at time t and α_t refers to year-by-month fixed effects. We consider a sub-sample consisting of units that are transacted multiple times, which allows us to control for unit fixed effects, η_i.

4.2 The appraisal value as a measure of expected selling price

We use the appraisal value as a benchmark to measure the normal market value of a unit. This section is dedicated to substantiating the choice of appraisal value as a gauge of market price.

Sell-appraisal distribution

In Figure B.2 in Appendix B, we plot a histogram of the sell-appraisal distribution. It is clear that the sell-appraisal spread is relatively symmetrically distributed around zero, with a large mass at zero. This pattern indicates that the appraisal value is an unbiased predictor of the sell price. A simple regression of the sell price on the appraisal value yields an R^2 of 0.9609, further bolstering this claim.

Price growth and low ask

Since the appraisal value is set before the unit is listed for sale, one potential concern could be that there may be very few units with low ask prices when house prices are increasing, simply because the ask price is set after the appraisal value. Conversely, in market with decreasing prices, one potential concern could be that ask prices tend be lie below the appraisal value, not because of seller decisions but because of market developments. To investigate these concerns, we inspect Figure B.3 in the Appendix B, which shows the fraction of units with an ask price below the appraisal value (measured on the left y-axis) against the median house price growth (measured on the right y-axis). These concerns can be put to rest. If anything, the pattern we detect indicates the opposite: that more units are listed with a low ask price in a rising market than in a falling market.

4.3 Unobserved heterogeneity

Unobserved unit heterogeneity

We define a strategic ask price as one that is set below the appraisal value and our assumption is that the observed difference between the ask price and the appraisal value is the result of strategic price-setting, not other causes. It is, however, possible to raise the concern that for some units the appraisal value might be off the latent market value. Some appraisal values might be set to high, others too low. The former may appear as a strategic price if the ask price reflects the latent market value. Such an error would not be offset by cases in which the appraisal value is too low while the ask price reflects the latent market value because these cases would not be characterized as strategic ask prices. This concern is not farfetched.

A high appraisal would be the result if there exist quality aspects that are not observed by the appraiser, but are nevertheless known to the seller and the real estate agent. One example could be a not easily detected need for renovation. The implication is a bias caused by unobserved heterogeneity. In order to investigate this possibility, we have acquired a data set of homes that have been renovated and in which we know the year of renovation. To explore whether there is a difference between the group of units that have an ask price below the appraisal value and the group of units that have an ask price greater than, or equal to, the appraisal value, we look at changes in renovation frequencies in the years preceding and succeeding the sales year. Results are summarized in Table B.2 in B. Our thinking is that if the concern is warranted we would observe an increase in renovation after a transaction since the buyer would detect the need. It is clear from the table that there is no significant differences in renovation frequencies in the year when the unit is sold. The same holds true for the years preceding a sale and for the years succeeding a sale. In order to control fully for unobserved unit heterogeneity, we also employ a unit fixed effect approach.

Unobserved seller heterogeneity

It is also possible to raise the concern that what we characterize as a strategic choice of a seller is not a strategic choice but rather reflects an inherent trait of the seller. Assume two kinds of sellers, one is patient and another one is impatient. It is fathomable, even if not necessarily plausible, that an impatient seller tends to both set the ask price below the appraisal and accept a low bid too soon. If so, the impatient seller would more often than the patient seller be involved in sales that appear to have strategic ask prices and that obtain a low sell price compared to the appraisal value. This unobserved seller heterogeneity would bias our results towards strengthening the negative effect of a low ask price on the sell price. We attempt to deal with this possibility in several ways. First, we investigate the distance between opening bid and accepted bid. Impatience would imply a lower distance. Thus, a latent personality trait that implied both low ask price and acceptance of low bid implies an association between a low ask price and a reduced distance between opening bid and accepted bid. We do not find this. Second, it is reasonable to believe that impatience would affect time-on-market. We find no difference between TOMs of units with low ask price compared to units with ask price equal to or greater than appraisal value. Third, we employ an instrumental variable approach in which we project the decision to use a low ask price to a plane orthogonal to type.

Unobserved realtor heterogeneity

Moreover, it is also possible to raise the additional concern about unobserved realtor heterogeneity. It is possible that a relation between low ask price and low sell price is caused by a realtor's lack of skill, not the strategy in itself. For the strategy of a low ask price to be demonstrably worse than an ask price equal to the appraisal value, one needs to control for realtor skill. We do that by including realtor fixed effects in our regressions.

4.4 Results

Table 3 tabulates results based on estimating (6) for different outcome variables. There are 4,354 units in our data that are sold at leat twice. In the first column, we report results when the dependent variable is the number of individuals who have signed up as being interested at the public showing. We see that offering a lower ask price increases the interest. The sign of the coefficient estimate of number of viewers is positive, but it is not statistically significant. In the next column, we see that offering a lower ask also leads to more bidders. The coefficient estimate is 0.033 and it is statistically significant. The interpretation uses the definition of the dependent variable given above, in which we insert a negative value of the ask-appraisal spread in order ease the interpretation. A lower ask price increases "a discount". Thus, the positive sign means that a larger discount is associated with a higher number of bidders, i.e. all else being equal, a lower ask price is associated with more bidders. In the third column, we estimate how the opening bid-appraisal spread is affected by using a low ask price. The coefficient estimate is -0.846. The interpretation is that one percentage point lower ask-appraisal spread is associated with 0.85 percentage point lower opening bid-appraisal spread.[12] This translates, essentially, into a relationship in which one percent lower ask price is associated with 0.85 percent lower opening bid since the denominators are identical, which implies almost full pass-through from the ask price to the opening bid.

The coefficient estimate of the sell-appraisal spread is -0.760 and statistically significant. A four percentage point reduction in the ask-appraisal spread is associated with three percentage point reduction in the sell-appraisal spread. Most of the reduction in the ask price appears to be found together with a reduction of the sell price. Nevertheless, the coefficient estimate of the sell-ask spread is 0.251 and statistically significant. If this estimated coefficient had been zero, a reduction of the ask price would not have been associated with a change in the sell-ask spread. Since the estiamted coefficient is statistically significantly different

[12] Or, since the spread is a fraction, a reduction of the ask-appraisal spread of 0.01 is associated with a reduction in the opening bid-appraisal of 0.0085. To ease reading, we use the term a "percentage point" as a reference to a fractional change of 0.01.

from zero, a four percentage point reduction in the ask price-appraisal spread is associated with a one percentage point increase in the sell-ask spread. This, we will argue below, is a useful result because it is consistent with the hypothesis that a manipulation of the ask price affects the sell-ask spread. We argue below that realtors tend to use their track-record of sell-ask spreads in the recruitment of new clients.

In the sixth column, we see that the coefficient estimate of the effect on TOM is 0.922 and statistically significant. The sign implies that a reduction in the ask price (a larger discount) is associated with an increase in TOM. This finding means that the notion that sellers tend to reduce the ask price in order to speed up the sale is not supported by data. In fact, with an ask price 10% below the appraisal value, our results suggest that the TOM increases by about 9 days.

The overall impression of these regressions is that we find statistically significant estimated coefficients and the explanatory power is high. For the sell-ask spread regression, the adjusted R2 is 0.916, which is considerable when one takes into account that the variation in the ask price explains much of the variation in the sell price. Thus, the spread is a residual. Nevertheless, running a regression with this residual, the part of a sell price not explained by the ask price, yields results that allows us to explain much of the residual variation.

We also see that the anchoring effect dominates the herding effect. Even if a lower ask is found to covary with more interest and a higher number of bidders, a lower ask also covaries with a lower opening bid. Since the latter is stronger, the total effect is negative: a lower ask price is associated with a lower sell price. However, keep in mind that a lower ask price is found to covary with a higher sell-ask spread. We shall explore this finding in detail below, as we will argue that it may help explain the existence of strategic ask prices.

Table 3: Low ask and auction dynamics. Units sold at least twice. 2007–2015.

	No. viewers	No. bidders	Op. bid	Sell-App.	Sell-Ask.	TOM
$-\frac{Ask_{i,t}-Appraisal_{i,t}}{Appraisal_{i,t}}$	0.041	0.033***	-0.846***	-0.760***	0.251***	0.922***
	(0.037)	(0.010)	(0.043)	(0.048)	(0.049)	(0.176)
N	4354	4354	4348	4354	4354	4354
R2	0.824	0.727	0.907	0.916	0.758	0.727
Controls:						
Common debt	✓	✓	✓	✓	✓	✓
Appraisal	✓	✓	✓	✓	✓	✓
Realtor FE	✓	✓	✓	✓	✓	✓
Realtor office FE	✓	✓	✓	✓	✓	✓
Year-by-month FE	✓	✓	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓	✓	✓

Notes: The table shows how different auction outcomes are affected by increasing the offered discount (lowering the ask relative to the appraisal value). The sample covers the period 2007–2015. We consider only units that are sold at least twice, so that we can control for unit fixed effects. In addition, we control for common debt and the appraisal value, as well as realtor fixed effects, realtor office fixed effects, and year-by-month fixed effects.

5 The role of the realtors

5.1 Model of realtor two-period profit-maximization

In a simple model, the realtor maximizes profits over two periods, the present and the future. Realtors compete over contracts and sellers screen realtors in order to find the best. The realtors come in two skill-types, T, good (G) and bad (B). The realtor knows his own type, but the seller does not. A realtor enters into a second-period contract after the completion of a first-period sale. A given realtor, r, knows that the first-period sell price $S_{1,r}$ and ask price $A_{1,r}$ affect the probability of obtaining a contract in the second period, since the seller uses the realtor's first-period sell-ask spread $SA_{1,r} = \frac{S_{1,r}-A_{1,r}}{A_1}$ as a performance metric in screening for a realtor. Realtors report their sell-ask spreads and the seller observes them.

Assume an unobserved density $f(P_h)$ for the sell price of house h across all realtors and all auction combinations of buyers. Define the market value, $P_h^\star$, as the expected value of this density, $P_h^\star = E(f(P_h))$. If $f(P_h)^\star$ was known, the seller in the second period would use $P_h^\star$, as a first-period performance-metric of realtor r. This spread, $SE_h = \frac{P_{h,1,r}-P_h^\star}{P_h^\star}$, is termed the sell-expected spread for house h and realtor r. It would have been a natural statistic had it been observable. In the absence of $P_h^\star$, the sell-appraisal spread $SAPP_{h,1,r} = \frac{P_{h,1,r}-APP_{h,r}}{APP_{h,r}}$ is another candidate. This statistic, however, is not available to sellers.[13] Both sellers and realtors know that it is not available.

While the density $f(P_h)$ and $\frac{P_{h,1,r}-P_h^\star}{P_h^\star}$ are unobservable, the sell-ask spread, $SA_{h,1,r} = \frac{P_{h,1,r}-A_{h,1,r}}{A_{h,1,r}}$, is observable. It affects the probability of obtaining a second-period contract for house j for realtor r, $q_{j,2,r} = q_r(SA_{h,1,r})$, in which q_r is an unspecified function that is monotonic in $SA_{h,1,r}$. The sell price $P_{h,1,r}$ is affected by the same-period ask price $A_{h,1,r}$ and the latent skill of the realtor type, $P_{h,1,r} = g(A_{h,1,r}, T_r)$. We do not specify the function $g()$.

In period one, the realtor seeks to maximize the present value of expected profits, given by:

$$\pi = \pi_1(R(P_1(A_1, T))) + \delta q \pi_2(R(P_2(A_2, T))), \tag{7}$$

in which we here, and onwards, for simplicity suppress realtor subscript r and house subscripts h and j. δ is a discount factor. R() is an unspecified revenue function that maps from the sell price to realtor revenue. The profit function $\pi()$ maps from revenue to profits, but we do not detail realtor costs. Using backward-induction, the realtor computes $\pi_2^\star = \max\ \pi_2(R(P_2(A_2, T)$. Inserting the solution into the present value formula reduces the two-period problem to a one-period maximization problem:

$$max(\pi) = max(\pi_1(R(P_1(A_1, T)) + \delta q \pi_2^\star). \tag{8}$$

The realtor's profits from the first sale $\pi_1(P_1)$ is a monotone function of revenue, which is a monotone function of the sell price in the first period P_1.[14]

The second-period probability of obtaining a contract, q, depends on the sell-ask spread in the first period, so that $q = q(SA_1(P_1(A_1, T), A_1, T)$. Thus, the realtor knows that his advice of ask price affects the same-period sell-ask spread directly through the ask price and indirectly through the sell price. The first-period sell-ask spread, in turn, affects the probability of obtaining the second-period contract.

[13] The appraisal value is not part of the public record in the transaction registry.

[14] In Norwegian real estate auctions, the commission fee may consist of a fixed fee component and a fraction of the sell price. Regulations require the fraction to be constant. Incentives schemes in which the commission is a proportion of the sell-ask spread or a step-wise function of fractions above a threshold of are no longer allowed.

$$\pi(P_1, A_1, T) = \pi_1(R(P_1(A_1, T))) + \delta q(SA_1(P_1(A_1, T), A_1, T))\pi_2^\star, \tag{9}$$

The partial derivative of the two-period profit function with respect to the first-period ask price, A_1 is:

$$\frac{\partial \pi}{\partial A_1} = \frac{\partial \pi_1}{\partial R}\frac{\partial R}{\partial P_1}\frac{\partial P_1}{\partial A_1} + \delta(\frac{\partial q}{\partial SA_1}\frac{\partial SA_1}{\partial P_1}\frac{\partial P_1}{\partial A_1} + \frac{\partial q}{\partial SA_1}\frac{\partial SA_1}{\partial A_1})\pi_2^\star, \tag{10}$$

in which we have suppressed that these partial derivatives are functions of the sell price, the ask price, and realtor type.

The partial derivative of the two-period profit function with respect to the first-period ask price consists of three terms. The first term is the effect on first-period profits from a change in the first-period ask price. The term consists of three factors. The first factor (right-most) is the change in the first-period sell price from a change in the first-period ask price. The second factor is the change in the first-period revenue from the first-period sell price. The third factor is the change in first-period profits from a change in first-period revenue. The second and third factors are positive. Our results also suggest that the sign of the first factor is positive, so the first term is positive.

The second term is the effect on the probability of obtaining a second-period contract through three factors. The first factor (right-most) is the change in the first-period sell price from a change in the first-period ask price. The second factor is the change in the first-period sell-ask spread from a change in the first-period sell price. The third factor is the change in the second-period contract probability from a change in the first-period sell-ask spread. The second and third factors are positive. Again, our results suggest that the sign of the first factor is positive, so that the second term is also positive.

The third term is the effect on the probability of obtaining a second-period contract through two factors. The first factor (right-most) is the change in the first-period sell-ask spread from a change in the first-period ask price. The second factor is the change in the probability from a change in the sell-ask spread. The first factor is negative and the second factor is positive so the third term is unambiguously negative. This effect is an incentive for a realtor to reduce the first-period ask price.

The total effect on profits depends on the relative magnitudes of the first two terms versus the last term. Our empirical program is to estimate the net effect. Since the partial derivatives are functions of realtor type, we will also explore differences across realtors.

5.2 Empirical results

What characterizes realtors who are involved in sales with low ask prices?

Our results suggest that a lower ask price is associated with a lower sell price. Causality aside, about 50 percent of the transactions are listed with an ask price that is below the appraisal value. In this section, we explore the co-existence of these two phenomena. We have mentioned above that a lower ask price is also associated with a higher sell-ask spread since a reduction in ask price is not fully passed-through into a similar-sized reduction of the sell price. This spread functions as a marketing device for real estate agents when they approach prospective clients in an attempt to signal skill. The implication is that realtors take into account not only how the ask price affects the current sell price, but also how it affects their track-record of the sell-ask spread. Since survey results, see Figure A.1 in Appendix A, suggest that survey responders trust advice from the real estate agent when they are making decisions on the ask price, it is plausible that sellers listen carefully to advice from realtors. Furthermore, as is shown in Figure A.2, survey responders also tend to believe that the realtor is instrumental to achieving the resulting sell price.

To investigate whether different realtors advise different strategies, we compare how the propensity to offer a low ask price is related to realtor performance. In our first approach, we partition each realtor's sales into two partitions by splitting by year. This leaves us with two partitions for each realtor for each year, $A_{r,t}$ and $B_{r,t}$. Then, we sum partitions A and partitions B across years for each realtor so that we obtain two samples for each realtor, A_r and B_r. Within each partition A or B, realtors are ranked according to how their median sell-appraisal spread score relative to other realtors' score in their partitions A or B. We rank using quintile groups. If the agent belongs to the first quintile in both partitions A and B, we characterize this realtor as "Very poor". If the realtor belongs to the highest quintile in both partitions, he is characterized as "Very good". By following this procedure, we get five categories of agents; {Very poor, Poor, Normal, Good, Very Good}. Agents who do not consistently belong to the same quintile across partitions A and B are discarded.

To explore whether realtor quality matters for the likelihood of offering an ask price below the appraisal value, we estimate the following logit-specification:

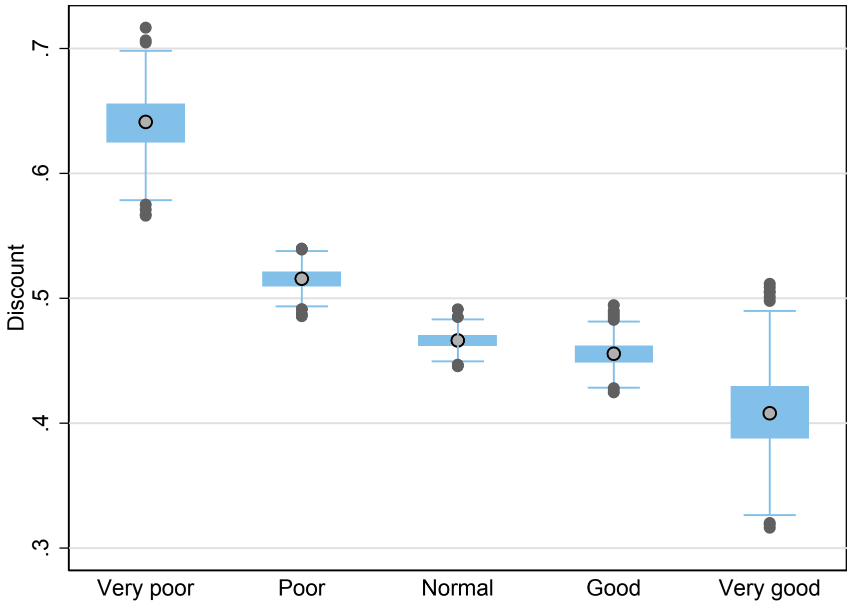
$$P[Ask_{i,t} < Appraisal_{i,t} | TimeFE, Type_i] = \frac{e^{\beta_t + \gamma' Type_i}}{1 + e^{\beta_t + \gamma' Type_i}},$$

in which

$$\text{Type}_i = \{\text{Very poor, Poor, Normal, Good, Very Good}\}.$$

Since the partitioning is random, we repeat this exercise 1000 times to perform a non-parametric Monte Carlo simulation of the estimation uncertainty. Box plots of the marginal effects for the likelihood of offering a low ask across the 1000 draws are summarized for each of the five categories in Figure 3. By visual inspect, we clearly detect a pattern. Very poor realtors are more likely to be associated with sales in which the ask price is below the appraisal value. Very good realtors tend to be associated with sales in which the ask price is equal to the appraisal value. In fact, the likelihood of offering a low ask price is monotonically decreasing in realtor quality.

Figure 3: Realtor quality and propensity to offer an ask price below the appraisal value.



Note: The figure shows box plots of the probability of being involved in sales with a low ask across different realtor types. For each agent and each year, we split the sample randomly in two. Then, samples are summed across years for each realtor. Within each of the two partitions, agents are ranked depending on their median sell-appraisal spread. We then rank realtors based on quintile grouping. If the realtor belongs to the same quintile in both partitions, he will be assigned a type. We repeat this exercise 1000 times to calculate bootstrapped confidence intervals.

Can realtors gain from advising low ask prices?

Our simple motivating model for realtor incentives in advising sellers on how to set the ask price suggests that there may be differences across realtor skill-types in whether advising a low ask price is a profit-maximizing strategy. To explore the hypothesis that realtor advice is related to realtor skill-type, we follow the same procedure as above. We characterize realtors' skill-level each year so that a given realtor in theory can change skill-type. This is done by random partitioning of each realtor r's yearly sales into two, $A_{r,t}$ and $B_{r,t}$ and characterizing a realtor as "High performing"/"Low performing"when both his A-sample and B-sample median sell-ask spreads are above/below the median across all realtors in that year. We repeat this procedure 1000 times in order to simulate the distribution of the estimates non-parametrically.

We then test whether being involved in a sale with a low ask price at time $t-1$ has an impact on number of sales (volume) and revenue in the subsequent period t. We study realtors who are classified as either High performing or Low performing in year $t-1$, and estimate the following equations for the two skill types:

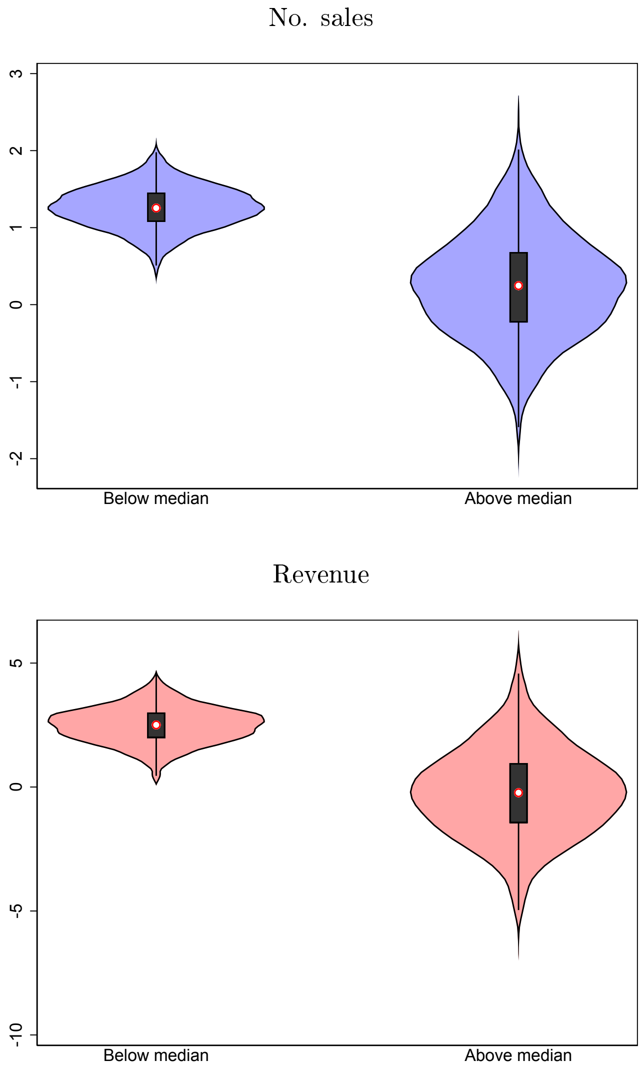
$$\Delta\text{No. sales}_{i,t}^{k} = \alpha^{k,m} + \beta_j^{k,m} + \eta_{l,t}^{k,m} + \gamma^{k,m}\left(\frac{-\left(Ask_i - Appraisal_i\right)}{Appraisal_i}\right)_{t-1}^{Median}$$
$$\Delta\text{Revenue}_{i,t}^{k} = \alpha^{k,m} + \beta_j^{k,m} + \eta_{l,t}^{k,m} + \gamma^{k,m}\left(\frac{-\left(Ask_i - Appraisal_i\right)}{Appraisal_i}\right)_{t-1}^{Median},$$

in which $k = \{\text{High performing}, \text{Low performing}\}$ at time $t-1$. α is an intercept, β represents realtor office fixed effects, while η represents of year-month-by-municipality fixed effects. The index i refers to the realtor, j to the office at which the realtor works, t to time, k to municipality, and m indicates that coefficients will vary across random draws. Our parameters of interest are $\gamma^{k,m}$, which measures the effect on number of sales and revenue of being associated with a low ask price at time $t-1$. Figure 4 shows violin plots for estimated coefficients for the two groups. The violin plots show the full density based on all 1000 procedures.[15]

Our results suggest that a low ask price at time $t-1$ is not associated with any effects on future sales and revenues for High performing realtors. In contrast, for Low performing realtors there is an association between being involved in sales with low ask prices and increases in next year sales and revenues. In particular, conditional on being a Low performing agent, we find that an increase in the median discount, i.e. a decrease in the ask price, by one percent is associated with an increase in next year's sales by two units, which in turn implies a revenue increase that is about NOK four million higher. Thus, there is a difference across realtor-skills to what extent being involved in sales with low ask prices in the current period is associated with increases in sales and revenues in the next period.

[15] Average coefficients and standard deviations based on the 1000 draws are are summarized in Table B.3 in Appendix B.

Figure 4: Realtor quality, ask prices and future performance

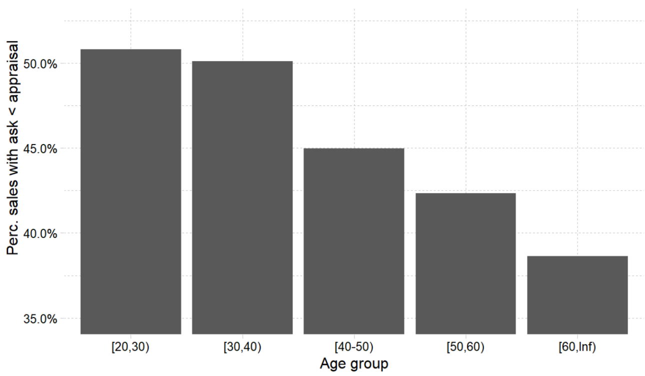


Note: The figure shows violin plots (the full distribution) for how a low ask in year t affects number of sales (upper panel) and revenue (lower panel) for two groups of realtors; those that in year t achieved a sell-appraisal spread above the median and those that got a sell-appraisal spread below the median. To rule out randomness, we split agent-year observations randomly in two, and require an agent to belong to the same group in both sub-samples to be part of the sample. This exercise is repeated 1000 times, so that we get a bootstrap estimate of the distributions.

5.3 Repeat-sellers: Do people learn?

Our results suggest that offering a low ask is consistent with a sub-optimal strategy for the seller. However, individual survey respondents report great trust in realtors, and certain realtors may gain from suggesting a low-ask price strategy. Do sellers never realize that low ask prices are associated with low sell prices or do they learn this over time. Since typical holding times can be 7-10 years for younger buyers, most buyers do not engage in many sales throughout their housing careers. Inexperience may be part of the explanation for the existence of the phenomenon. In Figure 5, we plot the frequency of units with an ask price below the appraisal value across different age groups. It is clear that it is more common to use low ask prices among young sellers than among older sellers.

Figure 5: Frequency of low ask prices across age groups



Note: The figure shows the frequency at which different age groups offer an ask price that is below the appraisal price.

To the extent that offering a low ask is more common among inexperienced sellers, one would expect sellers to update their strategies over time. To study whether and how sellers change their strategies over time, we have collected information from official registries of ownership to trace out the housing career of existing and past owners. We use these data to study whether previous sales experiences with a low ask price affects the strategy followed in subsequent sales. Results are summarized in Table 4. The variable of interest is the probability of employing an ask price below the appraisal value. The outcome variable is therefore a dummy taking the value one if the seller uses a strategic ask and zero otherwise. We estimate the binary choice model using both a probit approach and a linear probability model.

In constructing the independent variables, we distinguish between sellers that have previously used a strategic ask (Strategic, S) and sellers that previously used an ask price equal to the appraisal value (Normal, N). We then partition each of these into two sub-segments; those that succeeded (S) in the sense that they got a sell price in excess of the appraisal value and those that did not succeed (U). The four categories we consider are therefore: NU, NS, SS, and SU. We use NU as the reference category. In some of the specifications, we also control for the age of the seller, month fixed effects, year fixed effects, and unit type fixed effects (detached, semi-detached, row house, and apartment).

Results suggest that sellers who perviously used a strategic ask (independent of the outcome) are more likely to employ a strategic ask in their next sale than those that previously did not experiment with a strategic ask. This may be suggestive of differences in characteristics between sellers that employ strategic ask and those that do not. However, we also see that sellers who employed a strategic ask and achieved a sell price in excess of the appraisal value are more likely to continue with a low-ask strategy than sellers who previously used a low ask and did not get a sell price in excess of the appraisal value. Thus, there seems to be some evidence of learning among sellers in repeat transactions.

6 Robustness and sensitivity checks

Using a hedonic model to measure the market valuation

An alternative approach to using the appraisal value as an estimator of market value is using a hedonic model. We follow the conventional approach (Rosen, 1974; Cropper et al., 1988; Pope, 2008; von Graevenitz and Panduro, 2015) and consider a semi-log specification. As pointed out by e.g. Bajari et al. (2012) and von Graevenitz and Panduro (2015), hedonic models suffer from omitted variable-bias. This disadvantage is considerable compared to using the appraisal value, since a physical inspection by an appraiser involves inspection of the variables that are omitted in the hedonic model. The advantages, however, with using a hedonic model are two-fold. First, a model contains no risk of a strategic element, which could be the case with the appraisal value to the extent that the realtor and the appraiser cooperates. Second, the model contains no subjective elements or lack of market updating, which potentially could be the case for some appraisers. We summarize results from the hedonic regression model in Table B.5 in Appendix B. Results when we re-estimate the regressions for auction outcomes on low ask prices (discounts) when appraisal value is replaced by the model-predicted price are presented in Table B.6 in the same appendix. Results are robust to this alternative approach.

Table 4: Probability of ask price lower than appraisal value. Repeat sellers, 2002-2018, owners w/exactly 2 sales

	I	II	III	IV	V	VI
Model	Probit*	Probit	Probit	OLS	OLS	OLS
Intercept	-0.212	-0.225	0.010	0.416	0.412	0.502
	(0.009)	(0.140)	(0.140)	(0.004)	(0.050)	(0.050)
SS	0.324	0.321	0.279	0.128	0.125	0.108
	(0.014)	(0.014)	(0.015)	(0.006)	(0.006)	(0.006)
SU	0.268	0.256	0.247	0.106	0.100	0.096
	(0.013)	(0.013)	(0.013)	(0.005)	(0.005)	(0.005)
NS	-0.032	-0.036	-0.053	-0.012	-0.014	-0.017
	(0.013)	(0.013)	(0.013)	(0.005)	(0.005)	(0.005)
Seller age			-0.006			-0.002
			(0.0004)			(0.0001)
Month FE		YES	YES		YES	YES
Year FE		YES	YES		YES	YES
Unit type FE			YES			YES
		No. obs. 67,746				
AIC	92 604	90 960	90 511			
Adj. R^2				0.0149	0.0389	0.0454

Notes: The data are accessed by Eiendomsverdi into the registry of owners in Norway. We require that a realtor has been involved in the sale and that both ask price and appraisal value exist. The data span the period 1 Jan 2003 - 1 Feb 2018. Each unit owner is uniquely identified, but multiple owners are possible. We retained owners with owner-shares of 1/1, 1/2, 1/3, 2/3, 1/4, and 3/4. SS means that the seller tried strategic ask price in the first sale (ask price below appraisal value) and was successful (sell price above appraisal value). SU means that the seller tried strategic ask price in the first sale, but was unsuccessful (sell price below appraisal value). NS means that the seller set a normal ask price in the first sale and was successful. Unit type FE means that we employ four categories of unit type in which one is a default: detached, semi-detached, row house, and apartment. Probit is estimated using the GLM-function in R with family Binomial and the "Probit" link-function. Note that we did not employ seller FE models. * We also performed a non-parametric bootstrap simulation of the estimates in order to examine the GLM-procedure's sensitivity to sample outliers. We drew 1,000 same-size samples using sampling with replacement. We then estimated the for Model I all four coefficients for each of the 1,000 samples. were 0.0092, 0.014, 0.013, and 0.014, respectively.

Robustness to using full transaction level data

Our analysis has inputted bid logs and transaction level data from one firm, DNB Eiendom. Potentially, there may be biases in the type of units and type of clients DNB Eiendom handles. To examine to what extent this possibility appears to affect our results, we also acquired transaction level data from the firm Eiendomsverdi, a private firm that collects transaction data from all realtors in Norway and combines them with public registry information. Table B.8 summarizes the data. It is evident that the DNB Eiendom data appear to be similar to the full transaction level data. The main reason why we do not use the full transaction data set from Eiendomsverdi as our default is that they do not contain information on the individual bids of each individual auction. This lack of auction-specific information disallows investigations into elements of the herding effect such as number of bidders, number of bids, and the nominal value of the opening bid. The implication is that we cannot robustness check the herding effect results using Eiendomsverdi-data. Moreover, in the Eiendomsverdi-data we cannot control for realtor or realtor office fixed effects. However, as a robustness check, we have compared our results on the sell-appraisal spread, the ask-appraisal spread, and TOM from data from DNB Eiendom with data from Eiendomsverdi. None of our results are materially affected by choice of data source, and detailed results are reported in Table B.9 in Appendix B.

Compositional bias

The summary statistics in Table 1 shows that units sold with low ask prices tend to be smaller and more expensive. Apartments are represented more often among the sample of units with low ask prices. Low ask price units are sold in the capital city of Oslo with higher frequency. We investigate the sensitivity of our results to this potential compositional bias. In particular, we re-run the fixed-effects model and test the effect of increasing the discount on different auction outcomes for units that are priced below the median in their municipality versus units that are priced above the median. We also do a similar robustness test based on size-segmentation. Furthermore, we re-do all our calculations for using these segments: i) owner-occupied units, ii) houses (no apartments), and iii) units outside of Oslo. None of our results are sensitive to these segmentations and detailed results are reported in Table B.4 in Appendix B.

Variations over the housing cycle

To explore the sensitivity of our baseline results on auction outcomes to variations over time, we estimate (6) by allowing the coefficient on the discount variable to change from year-to-year. Box-plots over years for each of the variables are plotted in Figure B.4 in Appendix B. Although the effects on number of bidders and number of bids are less precisely estimated, all our findings are broadly robust to this exercise.

Non-linearities

There may be differences between offering a large and a small discount, i.e. set an ask price is much lower or only marginally lower than the appraisal value. To explore this possibility, we partition our data into 4 discount categories; Very small discount (0-3%), Small discount (3-5%), Large discount (5-10%) and Very large discount (above 10%). We then interact the discount variable with dummies for each of the categories. Results are summarized in Figure B.5 in Appendix B.

An instrumental variable approach

One potential concern is that there is a selection among sellers into deciding to offer a discount, so that only certain sellers, who also accepts lower sell prices, offer a discount, as mentioned above on unobserved seller heterogeneity. To deal with this, we employ an instrumental variable approach. We instrument the discount variable with the fraction of discounted units in the municipality in the quarter the seller is selling his unit. First stage results suggest that this is a strong instrument, and all our results are maintained in this case. Detailed results are shown in Table B.7 in Appendix B.

Different pricing strategies

There may exist multiple strategies in setting the ask price at a nominal level. For instance, if people search for houses in intervals, it may not be the percent discount that matters, but rather the nominal discount, i.e., whether lowering the ask price can contribute to attract other groups of customers. To explore this possibility, we study intervals of the appraisal value in NOK 100 thousands, in which all million-NOKs are converted to a round million. Thus, the first interval spans an appraisal value of NOK 1.05 million, an appraisal value of NOK 2 million, as well as NOK 3.09 million, etc. The next interval covers appraisal values of NOK 1.15 million, an appraisal value of NOK 2.19 million, as well as NOK 3.1 million, etc. Conditional on getting an appraisal value in a certain nominal window, the seller may opt for different strategies. We explore the following possibilities:

1. Setting the ask price equal to the appraisal value
2. Setting the ask price so that one targets the preceding interval (this strategy entails setting the ask no lower than 100K below the lower end of the appraisal interval
3. Setting the ask even lower than the preceding interval

4. Setting the ask within the interval

The frequency of these strategies for different windows are shown in Figure B.6 in Appendix B. The most common strategy is to set the ask equal to the appraisal. Interestingly, an exception can be found in the possibility that emerges with an appraisal value close to a round million. Then, the most common strategy is to set an ask price that is below the round million. To explore how the different strategies affect auction outcomes relative to setting the ask price equal to the appraisal value, we regress the outcome variables on dummies for the different intervals for each of the windows. We control for common debt, the size of the unit, the appraisal price, year-by-month fixed effects, zip-code fixed effects, realtor fixed effects, realtor office fixed effects and house type fixed effects. We are not able to control for unit fixed effects here, since very few units belong to the same appraisal window in two consecutive transactions. Estimated coefficients for each of the windows, for all variables, and for the three strategies are summarized in Figure B.7–**??** in Appendix B. For all windows, results suggest that the three strategies are sub-optimal relative to setting the ask price equal to the appraisal value. Thus, nominal discounts targeting certain windows are not associated with a higher sell price.

Fast sales?

One reason for setting the ask price low could be the intention to sell fast, i.e. achieve a low TOM. 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 TOMs for low ask prices.

7 Conclusion

We study price-setting and incentives in the housing market and ask two related questions: How does setting a low ask price affect the sell price? Why do people choose different strategies in setting the ask price? We construct a skeleton model that demonstrates that setting a low ask price generates two opposing effects, a positive herding effect and a negative anchoring effect. It is an empirical question what effect is stronger. If the answer to the first question is "no", one would expect that no sellers would use the strategy of setting the ask price low. Opposite, if the answer to the first question is "yes", one would expect all sellers to use the strategy of setting the ask price low. Yet it turns out that about fifty percent of the sellers use the strategy while fifty percent of the sellers do not. We construct a two-period model that shows that realtors face a trade-off between current profits and future profits. If the realtor advises a low ask price in the current period, and the sellers follow this advice, the result is a low sell price, which reduces current profits but increases future profits since it increases the sell-ask spread. The sell-ask spread is a marketing tool realtors use to recruit new clients.

We find that a low ask price is associated with a low sell price. Everything else being the same, a reduction in the ask price of 1 percent tends to be associated with a reduction in the sell price of 0.76 percent. The reason why is that the anchoring effect overwhelms the herding effect. We demonstrate that herding effect exists as a low ask price is associated with more visitors to the public showing and more bidders in the auction. The anchoring effect materializes through a lower opening bid. A 1 percent lower ask price is associated with a 0.85 percent lower opening bid, and this effect is the strongest.

At first blush, one could be tempted to think that nobody would choose a low ask price strategy. When we study what advice realtors offer sellers, we are able to trace out the contours of a possible explanation. The type of advice a realtor gives appears to be related to the type of the realtor giving the advice. This follows from our study of realtor skill. First, we characterize realtors by examining their score on a performance metric, the sell-appraisal spread. Then, we classify realtors who repeatedly score in the same quintile along a scale ranging from "Very poor" to "Very good". There is a monotonically falling relationship between the frequency of being associated with a low ask price sale and the performance metric. We then study why low-scoring realtors tend to be associated more frequently with low ask price sales. Part of the explanation is found by examining what happens to realtors next period after having been connected to sales with low ask prices this period. There is an association between low ask prices in the current period and an increase in sales and revenues in the future period for low-performing realtors. For high-performers, there is no association. Thus, it seems as if low-performing realtors maximize inter-temporal profits by advising clients to use low ask prices.

If the low-ask price strategy benefits low-performing realtors, but not sellers, one would expect sellers to detect it. However, even though a house is an asset with a considerable value, it is still an asset that sellers have little experience in selling. Individuals do not often sell a house. Using survey responses, we find that sellers tend to listen to and trust realtors. We do, however, detect some learning. By following sellers who have sold multiple times, we see that there is a slight tendency to change course subsequently to using an unsuccessful strategy.

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A Survey results

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

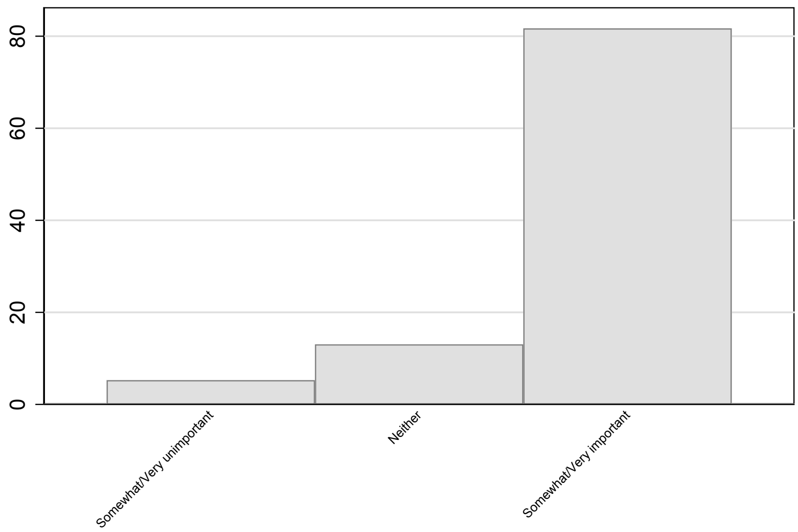


Figure A.2: How important is the realtor for the selling price?

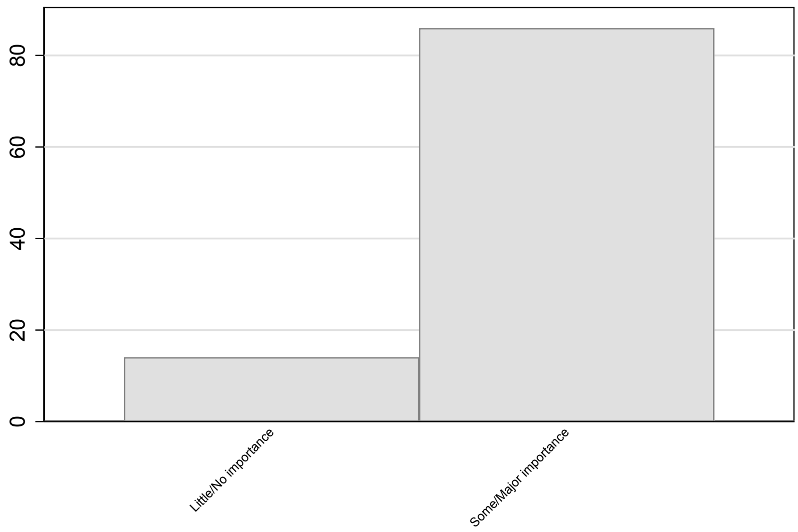


Figure A.3: What do you expect regarding the selling price when you buy?

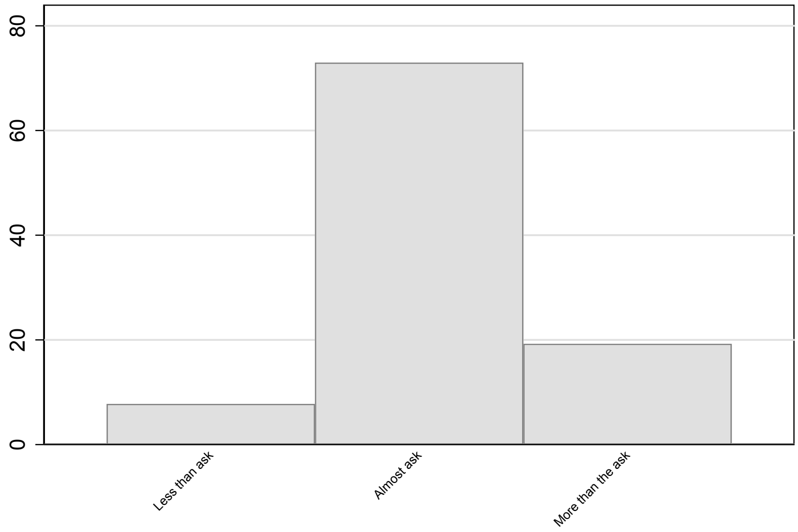


Figure A.4: Do you think a lower ask attracts more bidders?

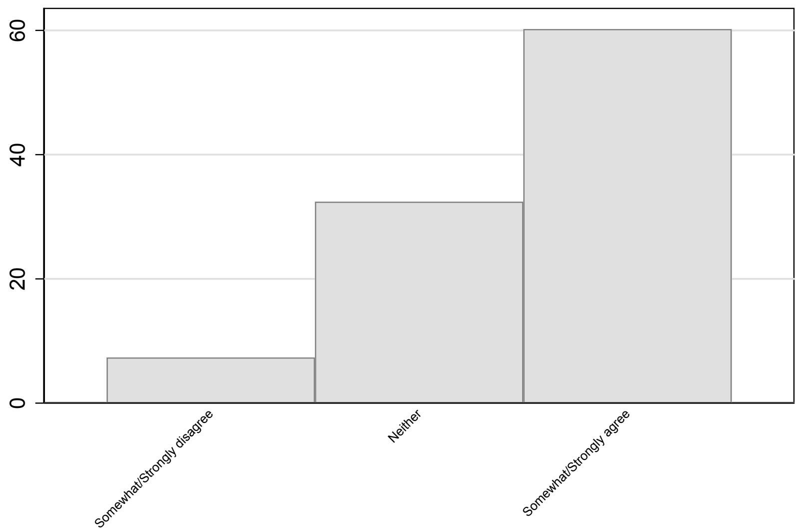


Figure A.5: Four houses are similar. You can only go to one viewing. The appraisal is 4.1 in all cases. Which viewing do you attend?

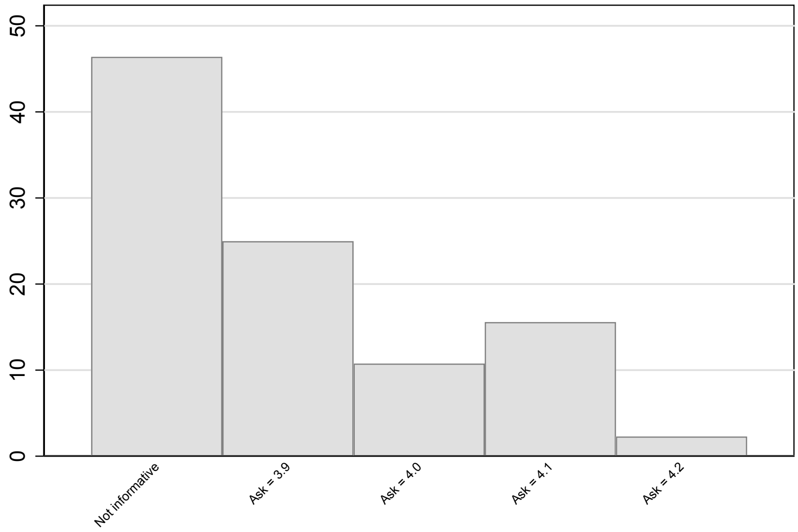
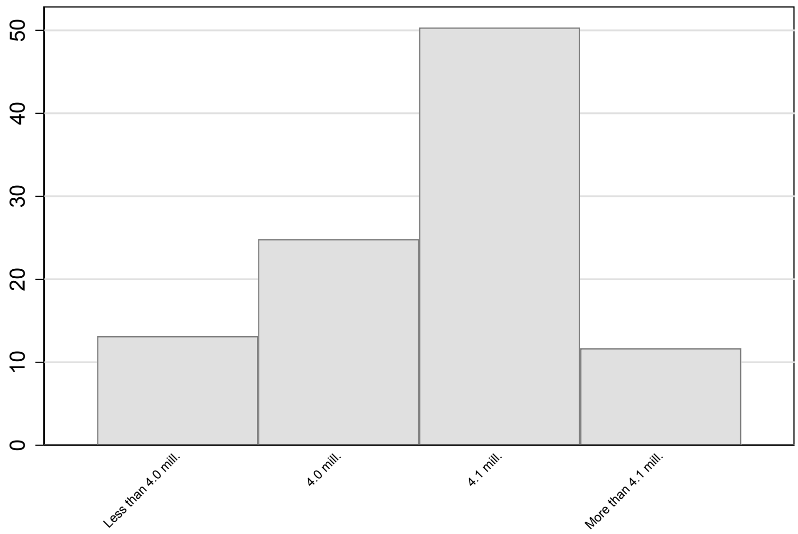


Figure A.6: Your house is valued at 4.1 million. What would you ask for?



B Additional results

Sell price, opening bid and number of bidders

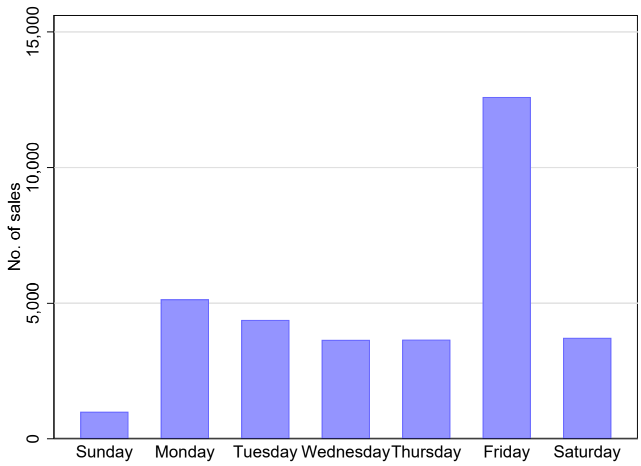
Table B.1: Regressing sell-appraisal spread on auction variables.

	(I)	(II)	(III)
No. bidders	2.256***		2.817***
	(0.112)		(0.094)
Opening bid		0.429***	0.562***
		(0.025)	(0.020)
N	4354	4348	4348
R2	0.923	0.918	0.949
Controls:			
Common debt	✓	✓	✓
Appraisal	✓	✓	✓
Realtor FE	✓	✓	✓
Realtor office FE	✓	✓	✓
Year-by-month FE	✓	✓	✓
Unit FE	✓	✓	✓

Notes: The table shows results from regressing the sell-appraisal spread on different auction variables; number of bidders, number of bids, and the distance between the opening bid and the appraisal value. All results are based on units that are sold at least twice, and all specifications include controls for common debt and the appraisal value, as well as realtor fixed effects, realtor office fixed effects, year-by-month fixed effects and unit fixed effects.

Day of advertising

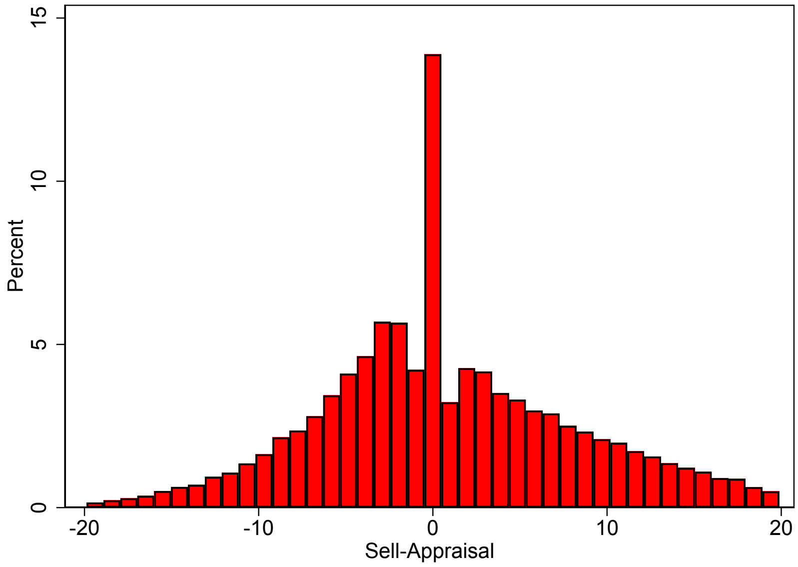
Figure B.1: Release day for online advertisement



Note: The figure shows a histogram for the day of online advertisement of units listed for sale in Norway.

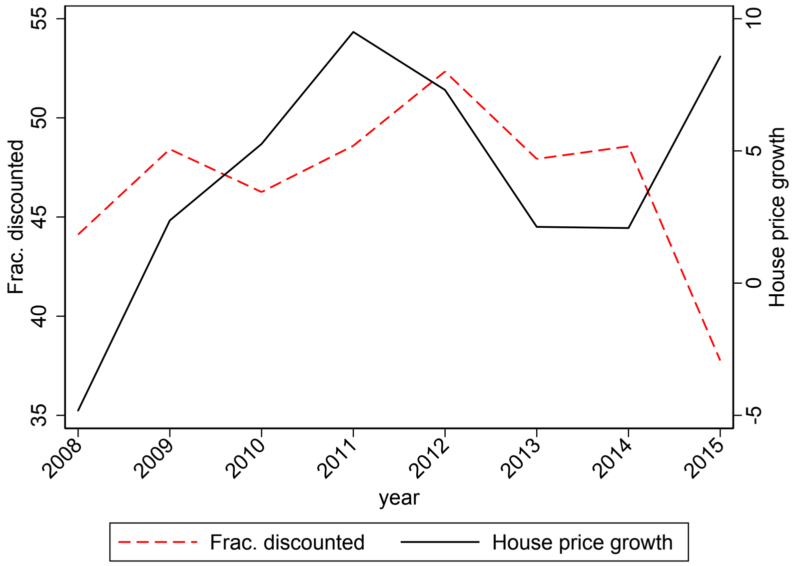
Appraisal validation

Figure B.2: Histogram of sell-appraisal spread



Note: The figure shows a histogram of the sell-appraisal spread for all transactions recorded in the auction level data. The sell-appraisal spread is truncated at -20% and 20% to get a better visual impression of the distribution.

Figure B.3: Percent units advertised with discount versus house price growth



Note: The figure shows the percentage number of transactions where a discount (ask lower than appraisal) is offered over time (left y-axis), as well as median house price growth (right y-axis).

Table B.2: Renovation frequencies around year of sale, discounted versus non-discounted units

	t-5	t-3	t-1	t	t+1	t+3	t+5
Discount	0.078***	0.092***	0.126***	0.153***	0.048***	0.022***	0.011***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
No discount	0.078***	0.086***	0.120***	0.149***	0.059***	0.023***	0.012***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
$p(H_0 : Disc. \leq Nodisc.)$	0.555	0.0437	0.0980	0.201	1.000	0.825	0.714
Observations	24,753	24,753	24,753	24,753	24,753	24,753	24,753

Notes: The table shows renovation frequencies in years prior to, in the year of, and in years after a sale takes place for both discounted units (ask lower than appraisal) and for non-discounted units (ask greater than, or equal to, appraisal). The table also reports p-values from a test of equal renovation frequencies among discounted and non-discounted units.

Realtor quality and future market shares

Table B.3: Discount strategy and future market shares.

	Below median		Above median	
	Δ No. sales	Δ Volume (mill. NOK)	Δ No. sales	Δ Volume (mill. NOK)
Discount$_{t-1}$	1.263***	2.490***	0.248	-0.225
	(0.276)	(0.751)	(0.683)	(1.838)
Time FE	YES	YES	YES	YES
Realtor office FE	YES	YES	YES	YES
Observations	443	443	460	460

Compositional bias

Table B.4: Compositional bias.

	No. obs.	No. viewers	No. bidders	Op. bid	Sell-App.	Sell-Ask.	TOM
Baseline	4354	0.041	0.033***	-0.846***	-0.760***	0.251***	0.922***
		(0.037)	(0.010)	(0.043)	(0.048)	(0.049)	(0.176)
Norway ex. Oslo	2883	0.062*	0.018	-0.806***	-0.822***	0.180***	0.784***
		(0.037)	(0.011)	(0.052)	(0.056)	(0.057)	(0.232)
Ex. apartments	529	-4.404	0.329	-1.041	6.895	8.014	-1.270
		(.)	(.)	(.)	(.)	(.)	(.)
Owner occ.	2298	0.037	0.050***	-0.814***	-0.718***	0.279***	0.625**
		(0.055)	(0.015)	(0.067)	(0.070)	(0.071)	(0.298)
Appraisal $\leq$ Median	2521	0.019	0.015	-0.778***	-0.733***	0.292***	1.377***
		(0.059)	(0.018)	(0.076)	(0.083)	(0.084)	(0.265)
Appraisal $>$ Median	847	0.095	0.052	-0.668***	-0.638***	0.344	1.735
		(0.137)	(0.046)	(0.222)	(0.206)	(0.210)	(1.319)
Size $\leq$ Median	3060	0.064	0.017	-0.803***	-0.754***	0.275***	1.018***
		(0.053)	(0.015)	(0.059)	(0.070)	(0.071)	(0.228)
Size $>$ Median	812	0.172	0.025	-0.844**	-0.680**	0.317	0.850
		(0.183)	(0.070)	(0.382)	(0.272)	(0.274)	(1.604)
TOM $\leq$ Median	969	0.045	-0.121	-0.782***	-0.960**	0.121	0.059
		(0.267)	(0.075)	(0.233)	(0.379)	(0.382)	(0.156)
TOM $>$ Median	726	-0.418	-0.122	-1.097**	-1.347***	-0.350	0.406
		(0.436)	(0.116)	(0.434)	(0.428)	(0.435)	(1.648)

Results from estimated hedonic model

Table B.5: Results from estimated hedonic model

	Sell
Constr. 1950-1980	-275.073
	(7434.079)
Constr. 1980-2000	225442.637***
	(8326.620)
Constr. 2000-	499050.225***
	(9079.204)
Lot size > 1000sqm	-6128.704
	(5677.520)
Apartment	0.000
	(.)
Detached	477593.476
	(673795.692)
Semi-detached	272476.469
	(673849.200)
Log(size)	-4617795.893***
	(230444.829)
$(Log(size))^2$	643564.734***
	(23662.969)
Log(size)× Apartment	-701489.800**
	(291422.912)
$(Log(size))^2 \times$ Apartment	161785.218***
	(31785.435)
Log(size)× Oslo	-1418879.541***
	(92249.427)
$(Log(size))^2 \times$ Oslo	282167.361***
	(10920.811)
N	64090
R2	0.827

Table B.6: Discount and outcomes. Using hedonic model to estimate market valuation.

	No. viewers	No. bidders	Op. bid	Sell-Pred.	Sell-Ask.	TOM
Discount	0.017***	0.006***	-0.894***	-0.978***	0.024***	0.061**
	(0.006)	(0.002)	(0.008)	(0.009)	(0.008)	(0.029)
N	4085	4085	4081	4085	4085	4085
R2	0.832	0.728	0.996	0.996	0.757	0.736
Controls:						
Common debt	✓	✓	✓	✓	✓	✓
Appraisal	✓	✓	✓	✓	✓	✓
Realtor FE	✓	✓	✓	✓	✓	✓
Realtor office FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓	✓	✓

An instrumental variable approach

Table B.7: Discount and outcomes. An instrumental variable approach.

	No. viewers	No. bidders	Op. bid	Sell-App.	Sell-Ask.	TOM
Discount	-0.002	0.035	-0.913***	-0.788***	0.200	1.451**
	(0.149)	(0.042)	(0.173)	(0.190)	(0.194)	(0.703)
N	4354	4354	4348	4354	4354	4354
R2	0.00781	0.0361	0.207	0.203	0.0421	0.0130
Controls:						
Common debt	✓	✓	✓	✓	✓	✓
Appraisal	✓	✓	✓	✓	✓	✓
Realtor FE	✓	✓	✓	✓	✓	✓
Realtor office FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓	✓	✓
First stage results:						
	Parsimonious	Fully specified				
Med. discount in mun.	1.005***	0.977***				
	(0.006)	(0.096)				
N	5009	4354				
R2	0.848	0.967				

Robustness to using full transaction level data

Table B.8: Summary statistics for full transaction data, discounted versus non-discounted units.

	Discounted		Non-discounted	
Variable	Mean	Std.	Mean	Std.
Sell (thou. USD)	428.4	214.3	416.71	229.6
Ask (thou. USD)	415.66	210.83	405.97	222.64
Appraisal (thou. USD)	430.75	218.1	404.94	222.63
Square footage	1011.69	513.81	1093.06	521.7
Discount (in %)	3.57	3.91	-.35	3.89
Sell-Appraisal (in %)	-.14	9.54	3.11	9.42
Sell-Ask (in %)	3.52	8.74	2.76	8.82
TOM	27.11	32.06	22.46	25.37
Perc. owner-occupied	63.13		67.3	
Perc. apartment	64.33		53.36	
Perc. Oslo	40.52		29.78	
No. observations	153719		168735	
No. auctions	158,123		177,427	

Notes: The table shows summary statistics for auction level data over the period 2007–2015. We partition between "Discounted" units (ask price lower than appraisal) and "Non-discounted" units (ask price greater than, or equal to, appraisal). For each of the sub-samples, the table shows the mean, median and standard deviation (Std.) of some key variables. NOK values are converted to USD using the average exchange rate between USD and NOK over the period 2007–2015, where $USD/NOK = 0.1639$

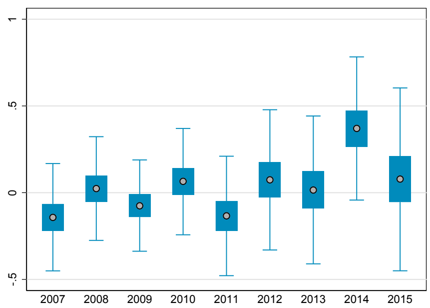
Table B.9: Discount and outcomes. Using transaction data for all real estate companies.

	Sell-App.	Sell-Ask	TOM
Discount	-0.670***	0.226***	0.769***
	(0.005)	(0.005)	(0.014)
Observations	174834	174834	174834
R2	0.473	0.397	0.454
Controls:			
Common debt	✓	✓	✓
Appraisal	✓	✓	✓
Time FE	✓	✓	✓
Unit FE	✓	✓	✓

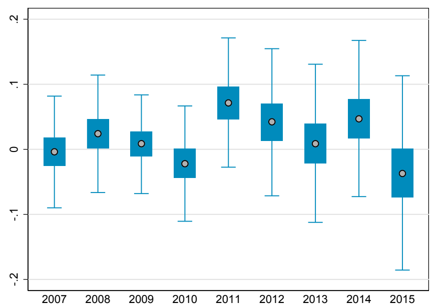
Variations over the housing cycle

Figure B.4: Time-variation in effect of discount on auction variables.

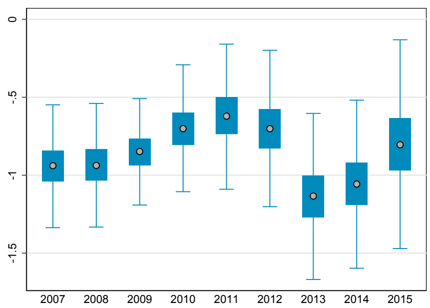
(a) No. interested



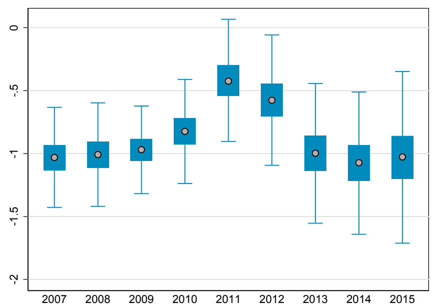
(b) No. bidders



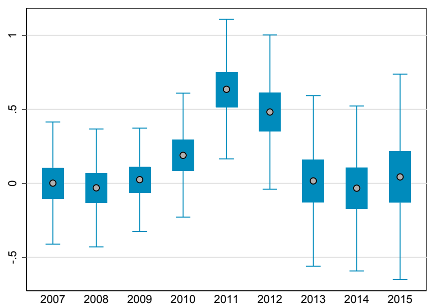
(c) Opening bid



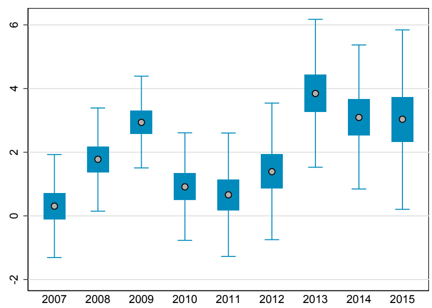
(d) Sell-appraisal



(e) Sell-ask



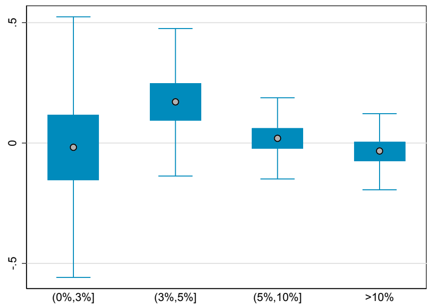
(f) TOM



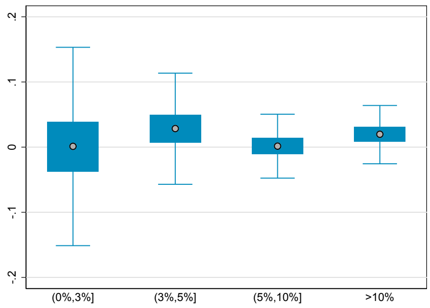
Non-linearities

Figure B.5: Non-linear effects of discount on auction variables.

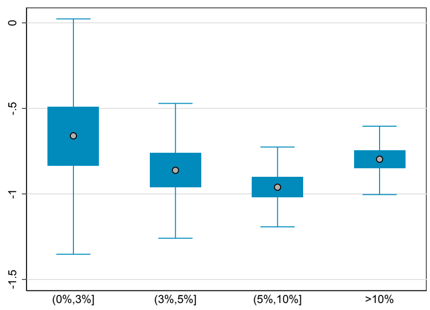
(a) No. interested



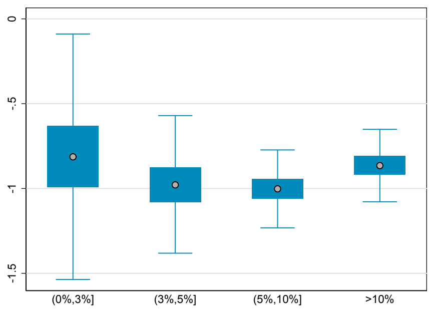
(b) No. bidders



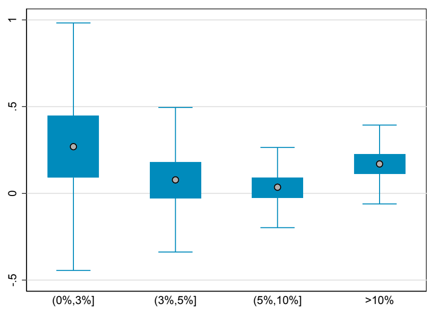
(c) Opening bid



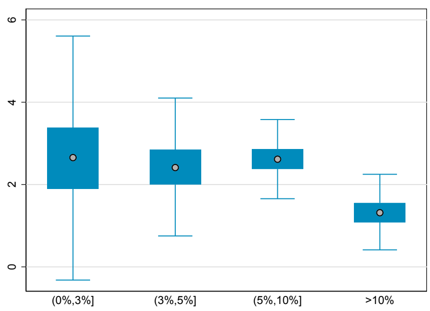
(d) Sell-appraisal



(e) Sell-ask



(f) TOM



Different pricing strategies

Figure B.6: Frequency of different strategies

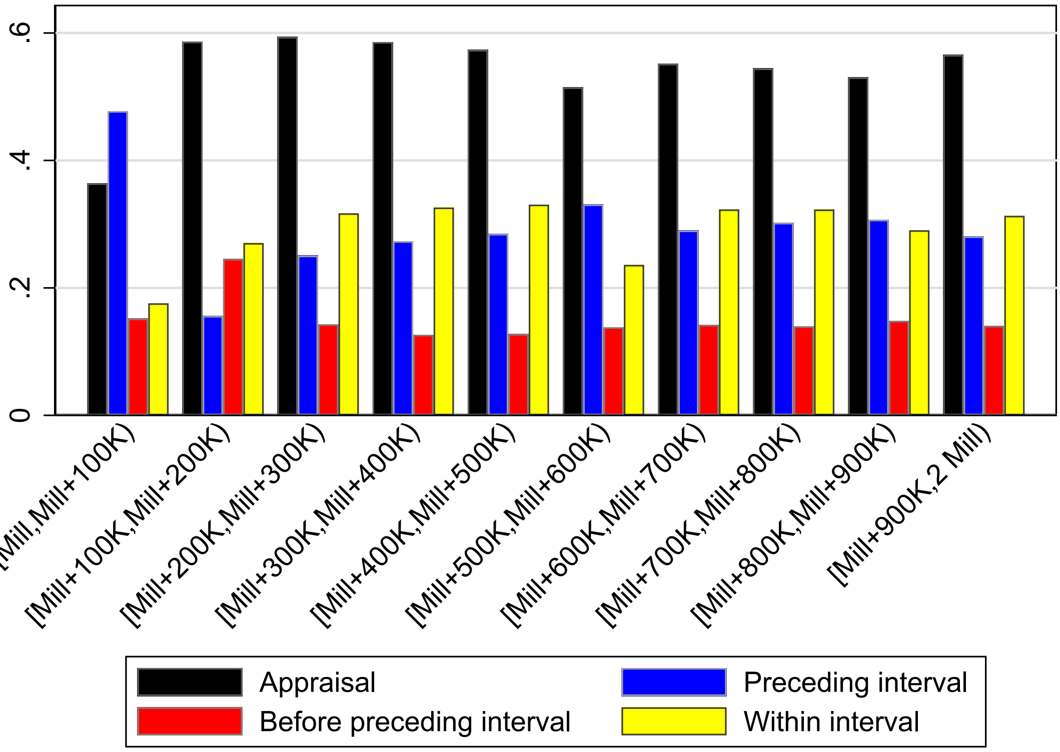


Figure B.7: Going up to 100K below interval. Effects relative to asking for appraisal.

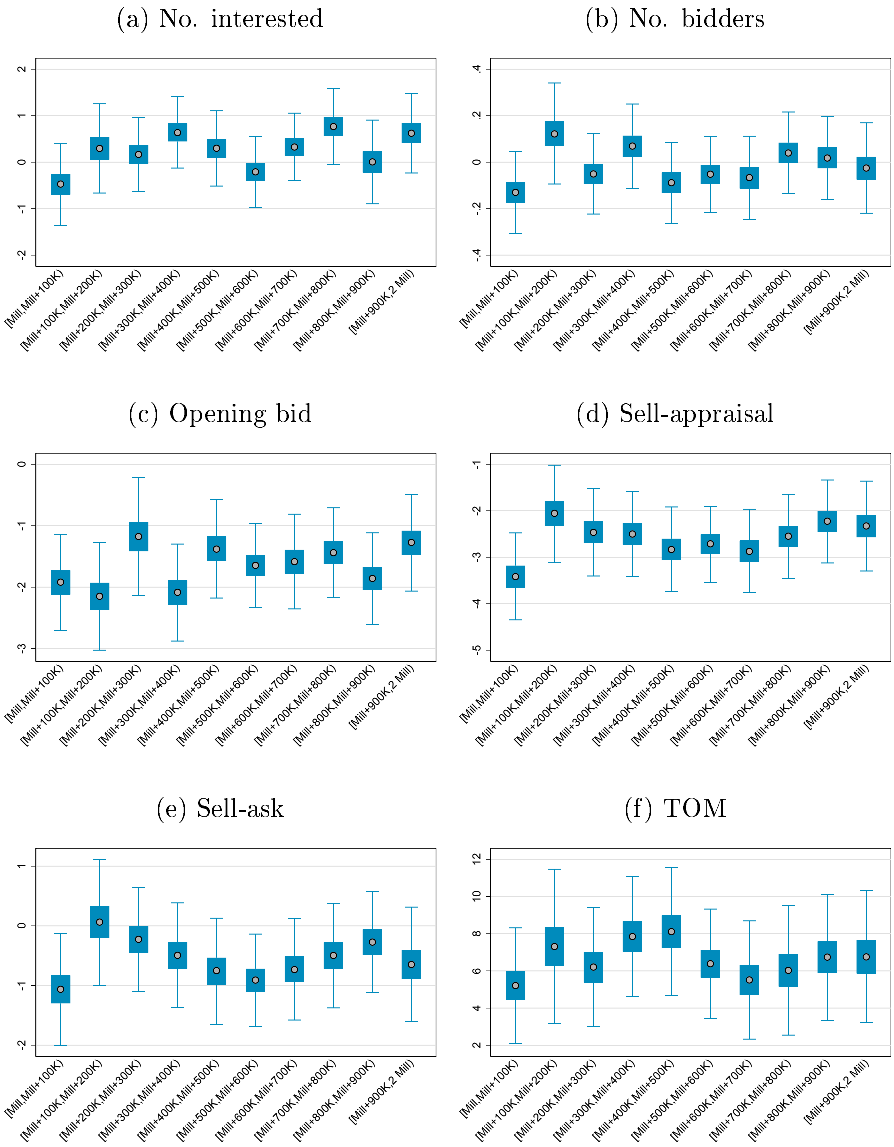
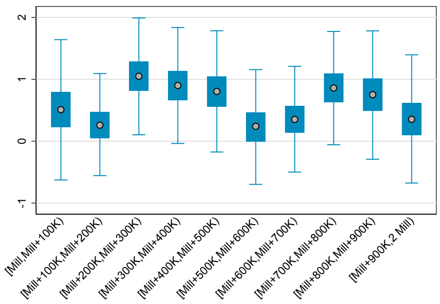
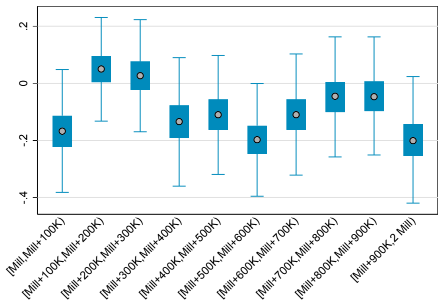


Figure B.8: Going up to 100K below interval. Effects relative to asking for appraisal.

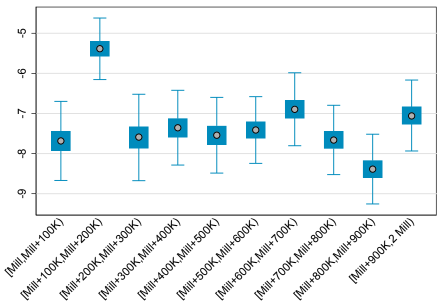
(a) No. interested



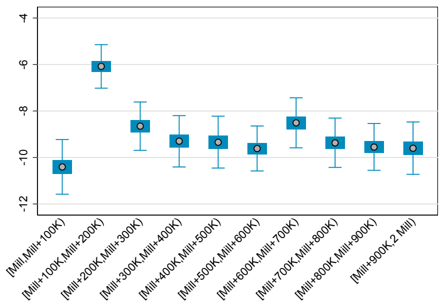
(b) No. bidders



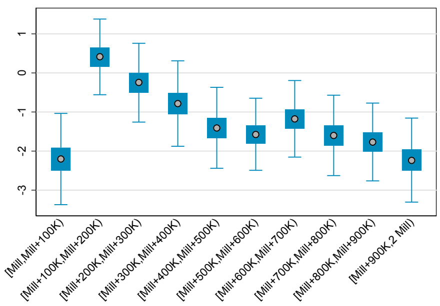
(c) Opening bid



(d) Sell-appraisal



(e) Sell-ask



(f) TOM

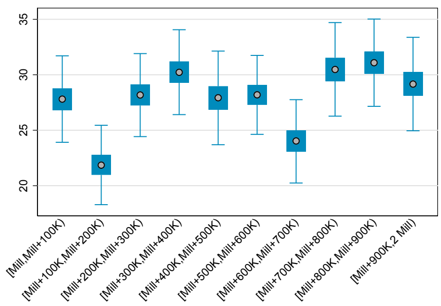
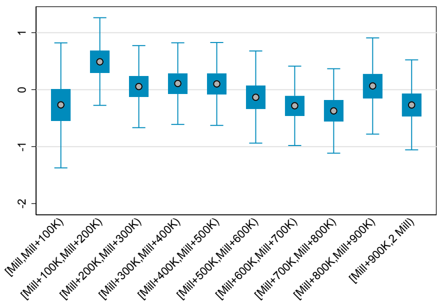
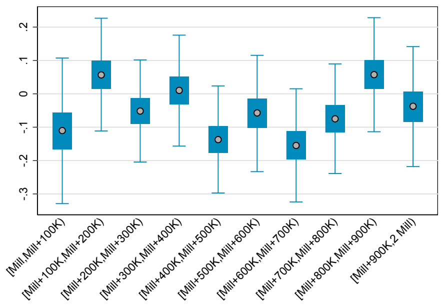


Figure B.9: Going below withing interval. Effects relative to asking for appraisal.

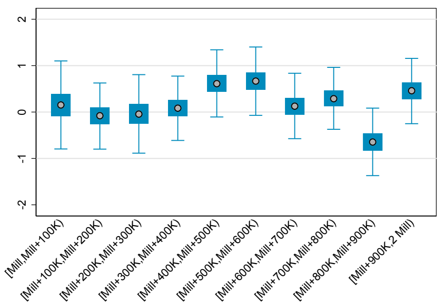
(a) No. interested



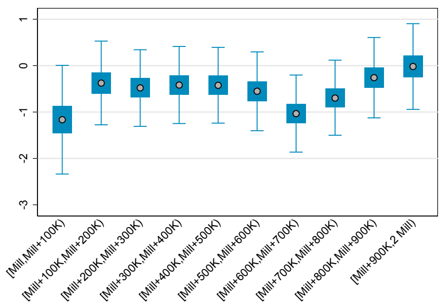
(b) No. bidders



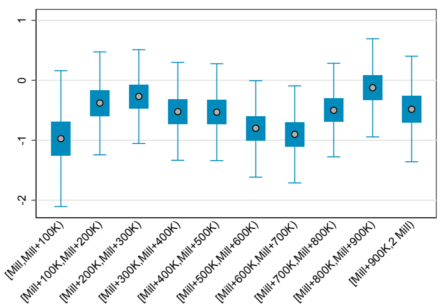
(c) Opening bid



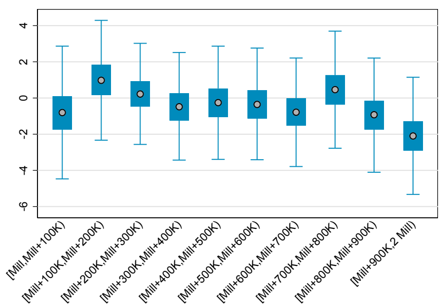
(d) Sell-appraisal



(e) Sell-ask



(f) TOM



Fast sales?

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.

Figure B.10: Survival rates after 100 days. Discounted versus Non-discounted.