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Abstract

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

Keywords: *Auctions; Bidding; Housing market; Principal-agent; Strategic pricing*

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

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1 Introduction

Price-setting is an activity economists take an interest in studying. Yet, many aspects of the price-setting process are not fully understood. One example can be found in the Norwegian housing market, in which many sellers set an ask price below an estimated market value. We believe that the phenomenon that some, but not all, sellers make use of a mark-dow strategy may be of broad interest since it contains evidence of strategic choices in the market place. If a lower ask price is optimal, then everyone would do it. If it is not, then nobody should do it. Yet about half of the sellers do it. This article seeks to uncover the explanation of this phenomenon by posing two related questions: How does setting a low ask price affect the sell price? Why do sellers choose different strategies in setting the ask price?

The short answer is that using a strategic mark-down reduces the sell price. We can say this because we exploit data on repeat-sales, repeat-sellers, and repeat-realtors that allow us to exploit observed variation and control for unobserved heterogeneity in units, sellers, and realtors. We also control for time-on-market, the business cycle, and geographical factors. To explain the different strategic choices, we follow realtors over time and classify them according to their score on a performance metric. We then see a clear difference in behavior. Low performance-score realtors tend to be associated with mark-down strategies to a higher degree than high performance-score realtors. We also show that among low performance-score realtors, those realtors who increase their mark-down tendencies are associated with an upward change in revenues in the subsequent year. There is no such revenue effect among high performance-score realtors. When we follow sellers over time and across sales, we observe that tendencies to use mark-down strategies are more infrequent among older sellers and sellers who have experienced unsuccessful mark-down attempts.

Our study of strategic price-setting and incentives in the housing market involves a principal-agent problem (Ross, 1973; Jensen and Meckling, 1976; Mirrlees, 1976; Lazear, 2018; Kadan et al., 2017) and signalling environments (Akerlof, 1970; Spence, 1973, 2002). The principal-agent problem arises because the realtor and the seller may not have aligned incentives. The signalling structure emerges both when there is a competition on message among sellers over prospective buyers and when there is competition among realtors over prospective clients. For a seller, the most powerful signal is the ask price. Set it too high and the seller scares away buyers. Set it too low and the seller tells the buyers that the unit is unattractive or that he is under financial duress. For a realtor, past performance is a signal of competence. Thus, a realtor seeks to show to sellers that he is able to achieve a high sell price compared to a yardstick. We show that the implication is that different types of realtors seek to affect the spread between the sell price and the ask price by targeting either the former or the latter.

Setting the ask price at the correct level is a key task for the seller. To get it right, the seller wants to consult a realtor, which in turn leads to a screening (Stiglitz, 1975; Riley, 2001) problem, namely to find the right realtor. The seller looks for observable evidence of skill and effort in order to screen realtors. This means that advising on the right ask price becomes a key task for the realtor, since the spread between sell price and ask price has an impact on the recruitment of future clients. Thus, setting the right ask price is something both the seller and the realtor seek to get right, but their goals are different: The seller wants a high sell price. The realtor wants a high sell-ask spread.

While the contribution of this paper is empirical, we start out by developing a skeleton model that outlines how sellers face a trade-off between a herding (Banerjee, 1992) and an anchoring (Tversky and Kahneman, 1974) effect when they set the ask price. The herding effect implies 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. It is an empirical question which effect is larger.

We use the appraisal value as a yardstick with which to gauge the outcome on sell prices. In Norway, 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 value. We explore how an ask price lower than the appraisal value affects the number of bidders, the opening bid, and the sell price. Since the natural default choice is to let the ask price be equal to the appraisal value, we define setting a lower ask price as a strategic mark-down. To control for unobserved heterogeneity, we use several tools. We follow units that are sold at least twice and include unit-fixed effects in our regressions. We follow realtors over time, so our regressions include realtor and realtor-office fixed effects. We also follow sellers over time. Our results show that the anchoring effect is considerable. In fact, an ask price one percent below the appraisal value tends to result in a sell price 0.9 percent below the counterfactual sell price that would have been achieved without the strategic mark-down. We also document a herding effect, but this effect is dominated by the anchoring effect.

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. 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, which leads 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 the seller to set a high or low ask price and demonstrate that the choice depends on the realtor's skills.

Our final investigation involves a study of repeat-sellers. We show that outcomes from past use of strategic mark-downs are associated with current use. The results indicate that sellers learn.

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, theoretically and empirically, to which extent results on signalling and principal-agent problems hold in a large-stake market such as the market for residential real estate.

We use a combination of Norwegian data sets. The 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 about 120,000 auctions and more than 750,000 bids during the period 2007-2015. We have 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 not only to study how the ask price affects bidding behavior in a given auction, but they also make it possible for us to follow repeat sales of the same housing unit. We can measure the performance of individual realtors across auctions. To study learning among sellers, we use repeat-seller information contained in official registry information on buyers and sellers in Norway. Finally, we were allowed to attach our own questions to an omnibus survey of households undertaken by Norway's largest bank, DNB. The main reason for collecting these survey data is to examine how buyers and sellers answer when they are questioned about the role of the ask price in housing auctions. Their answers shed light on the results from the bidding data. What the respondents say corroborate our findings.

Our analysis is confined to the Norwegian housing market. There are two main reasons for this. First, detailed data on the bidding-process have been systematically collected for a reasonably long time-period. Second, the institutional setting of the Norwegian housing market makes it well-suited for studying the effect of a strategic mark-down since sales are organized through classic ascending bid auctions. A typical sale 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 and this interest is recorded. All bids are legally binding. The acceptance of a bid is legally binding. Thus, at the minute the seller accepts a bid, transfer of ownership is essentially locked-in. The bidding activity takes place on digital platforms, which in turn implies that they are collected into data sets.

We perform several robustness checks and tests for alternative explanations for setting strategic mark-down. One motivation for using a strategic mark-down could be the intention to sell fast. Our results suggest that there is no association between the use of a strategic mark-down and the probability of fast sales. Most units are transacted within 100 days in Norway, so that the incentive to sell fast may be less relevant in Norway than in other countries with longer time-on-market (TOM). We explore the robustness of our findings along several dimensions. First, we test whether our results are robust to segmentation on size, price, house type, time-on-market, and location. They are. Second, 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. They do. Third, as an alternative way of measuring the ex ante market value, we estimate a hedonic model to gauge the market value of all units in the data set. Results are robust to this change of approach. Fourth, transaction level data 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 strategic mark-down is associated with a lower sell price is maintained in this larger data set. Fifth, we test for possible time-variation by redoing our analysis on a year-by-year basis. Our findings are robust to yearly segmentations. Sixth, potential non-linear effects of strategic mark-downs could arise if larger mark-downs are driving the results. We do not find evidence of this. Finally, we explore whether strategic mark-downs are prevalent for certain nominal price levels. For this purpose, we redo our analyses across the nominal price spectrum. None of our results are materially affected.

Literature review. Our paper contributes to several streams of the research literature. First, how to optimally set ask prices is a question multiple studies have posed. It is likely that sellers start out by contemplating their reservation price, but their ask price does not need to be identical to it (Horowitz, 1992; Taylor, 1999). Ask prices may also be linked to demand uncertainty (Herrin et al., 2004), the strength of the market (Haurin et al., 2013), and may serve a role in directing search (Han and Strange, 2015). 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 Norwegian 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 and that perhaps they are too trusting of their realtor. This is understandable given the infrequency of home-selling. A seller simply has little experience in selling his house.

Another stream followed the seminal study on anchoring by Tversky and Kahneman (1974). 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) suggest 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 study on loss aversion by Genesove and Mayer (2001). Our paper contributes to this literature by showing that a strategic mark-down curbs the opening-bid in housing auctions, which in turn lowers the sell price, suggesting that anchoring effects are present in housing auctions.

We add to the literature on bidding-behavior and herding. Ku et al. (2006) argue 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 strategic mark-down results in more bids. However, our results contain an additional, opposing effect, namely the anchoring effect. The net result of the two opposing effects is that a strategic mark-down implies a lower sell price.

In eBay-auctions, it has been documented that round number ask prices 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 (agent) and an agent (realtor) arise 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 for the seller, low-skilled realtors appear to display behavior consistent with a model in which they rationally advise sellers to mark down the ask price in order to expand their customer base and profits in the 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 he sets the ask price. In Section 3, we present the data and offer descriptive statistics. In the subsequent section, we discuss our empirical specification. Results on the effects of strategic mark-downs on auction dynamics and outcomes are presented in Section 5. In this section, we also discuss how we deal with unobserved heterogeneity and potential compositional bias. In Section 6, we present a motivating model for realtors' incentives when advising on ask prices. In the same section, we show that there are differences in the propensity to use a strategic mark-down among realtors and show that the effect of this strategy on future profits differ across realtor types. We also show that sellers learn as they gain more experience. Sensitivity and robustness checks are discussed in Section 7. The final section concludes and discusses some policy implications of our results. The appendix contains information on survey data, and further results.

2 Institutional background and a skeleton model

2.1 Institutional background

Realtors

Most sales of houses and apartments in Norway are brokered by a realtor, who is hired by the seller. In contrast to the practice in some other countries, the buyer does not hire a separate realtor in Norway. The Norwegian law requires the realtor 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 custom 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. A realtor's compensation scheme typically includes a variable fee, which is proportional to the sales price, and it amounts to approximately 1.5 percent.

Appraisers

Until 2016, a person who decided to sell his property, typically obtained an appraisal value from an appraiser.[1] The appraiser would inspect the home prior to the advertisement and write a technical report about the general condition of the unit. The report would include a description of the material standard, technical issues, and other information. For example, the appraiser would identify a need for drainage, measures of water pressure, and potential problems with moisture.[2] 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 value. This estimate would take into account both the market conditions and the technical elements of the unit. When a home was listed for sale, the appraisal value and the technical report were common knowledge to prospective buyers.[3]

The selling process

In Figure 1, we summarize the selling process in Norway. Having collected an estimate of the market value, the seller makes a decision – in collaboration with the realtor – on the ask price.

The seller may choose to set an ask price that is lower than, equal to, or higher than the estimated market value. The ask price is intended to reflect, or at least guide the buyer on, the reservation price of the seller at the time when the unit is *listed* for sale, but not necessarily at the time when the auction commences, since expectations may change over time.

The regulations that govern real estate transactions reflect the competing interests between, on the one hand, not requiring the seller to reveal an important strategic tool (his reservation price), and, on the other hand, disallow unfair marketing. The resulting regulation is a compromise that leaves intact the basic contractual principle that a seller can decline any and every bid, but also pro-

[1] From 2016 onwards, the value estimate is made by the realtor. 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 professional 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".

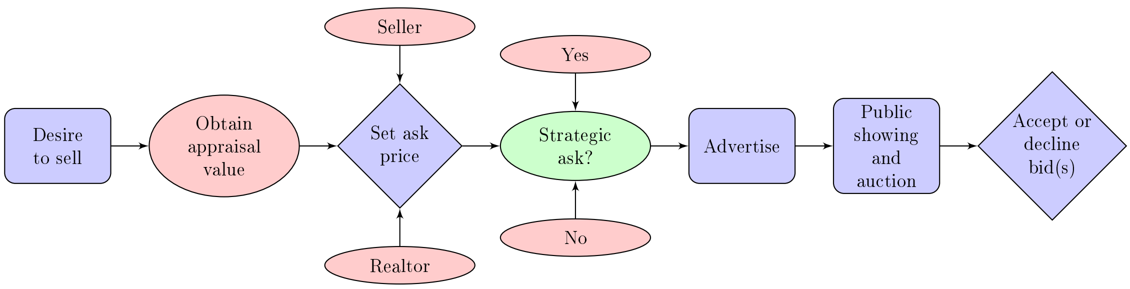
[2] For more information, see norsktakst.no or nito.no/english for online descriptions of Norwegian appraisers.

[3] 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.

tects the buyer by stating that authorities monitor realtors who are reported to be associated with multiple sales in which bids above the posted ask price were declined.

Thus, a seller is not obliged to accept a bid at, or even above, the ask price. For instance, the seller may update her beliefs about the market value of the unit conditional on number of viewers at the public showing, or general market developments, that leads her to reject offers at, or above, the initial ask price. The seller can even justify a decline of a bid due to a sudden change of mind. The seller is therefore legally positioned to choose an ask price strategically in an attempt to affect the outcome of the auction. However, the realtor faces some constraints in that he does not want to be associated with illegitimate ask prices. The realtor is aware that he cannot leave a track record that systematically, over multiple sales, shows a substantial discrepancy between the ask price and the sell price or a pattern that reveals that in multiple auctions bids above the posted ask price were rejected. In practice, the implications for the seller is that the law does not seriously limit the realistic range from which he can choose an ask price. The resulting impact on realtor behavior of this regulation is that the realtor is incentivized to avoid being associated with illegitimate ask prices.

Figure 1: The selling process



Notes: The figure illustrates a typical process, and is not meant as an exhaustive graph that captures all processes. Most importantly, we have not attempted to capture the sequencing decision a moving households must make, i.e., the decision of buying or selling first. Buying first implies owning two units in the transition process. Selling first implies not owning any units in the transition process. Even though most households most of the time, choose the former, the frequency of buy-first owner-occupiers to sell-first households is pro-cyclical (Anundsen and Røed Larsen, 2014). Moreover, in some cases, a bidder contacts the seller without going through the realtor and extends a bid directly to the seller. In addition, several nuances are not illustrated, for example the possibility of holding several public showings, the decision of deciding if both the realtor and seller should be present at the public showing, and the dynamic of the auction itself (including bids, bids with expiration, and counter-offers from the seller).

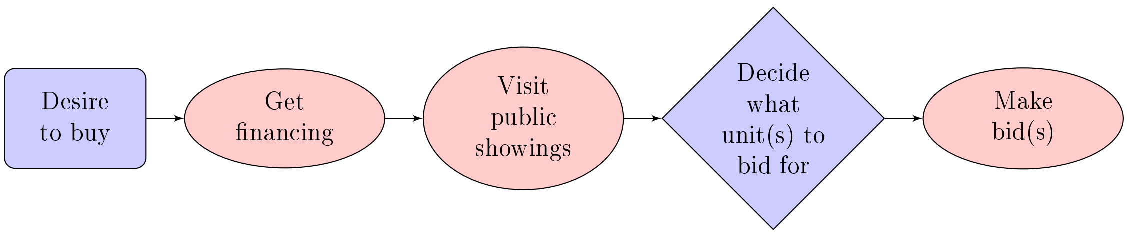
Having decided on the ask price, the seller posts the house for sale, typically using the nationwide online service Finn.no and national and local newspapers.

Most units are announced for sale on Fridays.[4] 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 week-end 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 directly to the seller prior to the public showing. Since most units are posted for sale on Fridays, there will be fierce competition among sellers to attract people to their public showing. Sellers may therefore use a strategic mark-down in competition with other sellers to attract more people to visit the public showing.

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 own and his household's income, debts and assets, and his status as married, single, or cohabiting with a partner. The bank assesses the financial ability of the applicant.[5] Conditional on financing, the search process begins. The proof of financing is not contingent on buying a particular unit – it reflects the maximum bid the buyer can make in any auction of any house. Loan-to-value is calculated based on actual sell prices, and not on the appraisal value.

Figure 2: The buying process



Notes: The figure illustrates a typical process, and is not meant as an exhaustive graph that captures all processes. The figure does not capture the buy-first or sell-first sequencing decision a household makes. It also does not offer any details on how to acquire financing by visiting several banks nor details on the multi-faceted search-and-match process of how to decide which public showings to visit on the basis of studying advertisements. We do not go into the possibility of constructing strategies of bidding.

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

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

[5] Starting in 2017, mortgage loans are more regulated. The regulation includes a passage that states an LTV-limit of 85 percent and a maximum (total) debt-to-income ratio of 5. In addition, banks need to comply with additional macro-prudential requirements.

interest, the buyer places his bid. Since each and every bid is legally binding, most buyers only bid for one unit at the time.[6]

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. Short expiration times are common, and 52 percent of the bids are placed with an expiry of less than one hour, and in auctions with more than one bidder, 53 percent of the bids are rivalled within 15 minutes. The full distribution of expiration times (in minutes) and time to a new bid is placed (in minutes) are shown in Figure B.4 and Figure B.5 in Appendix B

2.2 A skeleton model for a strategic mark-down

There is a growing literature on housing search (Diaz and Jerez, 2013, Ngai and Tenreyro, 2014, Head and Sun, 2014, Nenov et al., 2016, and Piazzesi and Stroebel, 2020). Han and Strange (2015) present an overview of studies into the microstructure of housing markets, including search. We follow Han and Strange (2016), and focus attention on the strategic use of the ask price. While their model shows how the ask price directs search, our model is constructed to shed light on two opposing effects generated by the ask price in a search environment.

Consider a housing market with N_B buyers and N_S sellers. Houses are both vertically and horizontally differentiated.[7] 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

[6] It is legal, and not uncommon, 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 a statement about access to financing.

[7] 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 everyone agrees on the ranking. Then, individual tastes matter and there is no agreement on what is preferable.

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 the description of some of the horizontally differentiated qualities, Q_h (e.g., location, color, building 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 the highest estimated latent match quality in combination with his financial constraints. A buyer only visits a house h if his estimated match-quality based on attributes AT_h combined with his financial position justifies it. In order to formalize the (open house) decision process, let I_b be short notation of buyer b's income, equity, and financial position. Furthermore, let $g = g(\tilde{M}_{b,h}; I_b)$ be a ranking function to be used for ranking whether or not different houses are worthy of a visit to the open house. This ranking function g is used in the following way. Let A_h be the ask price of house h and $D_{h,b} = 1$ 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. Then, $D_{h,b} = 1$ if:

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

There exists a threshold at which a marginally higher ask price A_h changes $D_{h,b}$ from 1 to 0. Thus, similar to Han and Strange (2015), our model also implies that the ask price directs search. 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 scores on the ranking function $g(\tilde{M}_{b,h}, I_b)$, 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 the threshold $\phi(A_h)$ is suppressed from the decision function. The ask price A_h is chosen by the seller and is 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 and impacts further search and matching, but the seller of house h does not 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 all 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 $\tilde{CV}_h$ based on the ask price A_h, and the number of visitors to the public showing 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, $WTP_{b,h}$ for buyer b, 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 buyer b's financial position:

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

in which we have suppressed the determinants for the private value in order to emphasize the dependency on ask price and dropped the financial constraint to ease notation. 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:

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

The total derivative of the willingness to pay with respect to the ask price contains two terms. The first term, $\frac{\partial WTP}{\partial \tilde{CV}} \frac{\partial \tilde{CV}}{\partial A}$, is the *direct* effect on the estimated common value of an ask price change. It has two factors. The first factor, $\frac{\partial WTP}{\partial \tilde{CV}}$, is positive. When the estimated common value increases, so does the willingness-to-pay. The second factor, $\frac{\partial \tilde{CV}}{\partial A}$, 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 effect from a change in ask price on the resulting change in the willingness-to-pay.[8]

3 Data and descriptive statistics

3.1 Bidding 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 in every auction that resulted in a sale and 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, the appraisal value, and attributes of the unit. Co-ops typically take on debt to renovate the exterior of buildings, remodel kitchens and bathrooms in the different apartment units belonging to the co-op.[9] This debt is called the "common debt", and each co-op owner is charged a monthly fee to service his share of that debt. We have data on this debt and control for it in the analysis.

The data set consists of 168,578 housing auctions, which in turn involve 1,079,744 bids. Since the appraisal value ceases to be obtained in 2016, we confine our analysis to the period 2007-2015. This leaves us with 133,881 auctions. We remove sales of units for which we do not now the address of the unit and all units transacted more than three times.[10]

[8] 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, if bidders anchor their WTP at a lower nominal level, this translates into a lower sell price. In other words, there are two opposing effects.

[9] There are also some cases in which non-coops do this, but this is much less common.

[10] Very few units are transacted more than three times using DNB Eiendom as the real estate agency. 67 units are reported to be transacted four times and 28 are sold five times. One unit is reported to be sold 13 times.

We remove units for which there is no information on the sell price or the ask price. Finally, we trim the data set on the 1^{st} and 99^{th} percentiles of the sell price, ask price, appraisal value, and size.[11] This leaves us with 120,383 auctions, which in turn involve 756,944 bids. Appraisal values are not reported in all cases,[12] and we are left with 75,908 auctions,[13] which involve 515,053 bids.

We extract information on each auction, 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 (strategic mark-down) 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 two bidders. This holds true for auctions with strategic mark-downs and auctions without strategic mark-downs. The opening bid is typically lower than the ask price and the appraisal value for both segments. However, for units with a strategic mark-down, 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 strategic mark-down results in a sell price that, on average, is below the appraisal value. In contrast, units with no strategic mark-down have a positive sell-appraisal spread.

In general, units with a strategic mark-down are smaller and cheaper, and apartments are represented more often than detached houses. Using strategic mark-down 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.

[11] Percentiles for sell price, ask price, and appraisal value are constructed for area and year. For size, percentiles are calculated for area, year and house type. Local areas are constructed by merging municipalities in order to ensure a sufficient level of transaction volume. The areas we study are: Oslo, Fredrikstad, Bærum, Asker, Skedsmo, Lillehammer, Bergen, and the rest of the country.

[12] For instance, appraisal values have historically not been used in Trondheim – Norway's third largest city.

[13] We use the term "auction" here even though the term "transaction" could be more apt for sales processes in which the time-on-market is very long and the resulting sales process entails a one-on-one negotiation between the seller and one single bidder.

Table 1: Summary statistics for auction-level data. Segmentation on the ask price-appraisal value differential. Norway, 2007–2015

	Ask price < Appraisal value		Ask price ≥ Appraisal value	
Variable	Mean	Std.	Mean	Std.
Sell price (in 1,000 USD)	429.50	202.52	416.95	216.46
Ask price (in 1,000 USD)	419.09	199.98	405.81	209.54
Appraisal value (in 1,000 USD)	435.91	207.80	404.60	209.23
Square footage	1069.11	548.89	1126.77	532.41
Strategic mark-down (in %)	3.87	4.43	-0.42	6.50
Sell-App. spr. (in %)	-1.07	9.93	3.29	10.56
Sell-Ask spr. (in %)	2.85	8.46	2.90	8.85
No. bidders	2.40	1.69	2.24	1.50
Op. bid-ask spr. (in %)	-6.71	6.68	-6.73	6.90
Op. bid-app. spr. (in %)	-10.27	7.94	-6.38	8.99
Op. bid-sell spr. (in %)	-8.99	7.25	-9.05	7.56
Perc. owner-occupied	65.72		71.64	
Perc. apartment	59.27		49.89	
Perc. Oslo	31.90		21.37	
No. auctions	35,149		40,759	

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 (strategic mark-down) 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 the exchange rate was $USD/NOK = 0.1639$.

3.2 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 realtors who are associated with auctions involving units with strategic mark-downs and how it affects their future sales, we construct a separate realtor data set. In Table 2, we summarize some key variables from this data set. It is evident that there are great variations in both number of sales per year and annual revenue across realtors.

Table 2: Summary statistics for realtor-level data. Norway, 2007–2015

Variable	10^{th} pct.	25^{th} pct.	Median	Mean	75^{th} pct.	90^{th} pct.
No. sales	6	13	24	25.74	36	48
Revenue (mill. USD)	2.53	4.88	9.54	10.89	14.83	20.88
No. years active	3	4	6	5.39	7	7
No. realtors				656		
No. offices.				120		

Notes: The table shows summary statistics for the realtor-level data over the period 2007–2015. The table shows the mean and median of some key variables, in addition to the 10^{th}, 25^{th}, 75^{th}, and 90^{th} percentiles. Only realtor-year observations in which realtors sell at least 4 units per year are kept.

3.3 Repeat-seller data

Through assistance by the private firm Eiendomsverdi AS, we have accessed transaction and owner databases over the period 1 January 2003 – 28 February 2018. Eiendomsverdi AS collects data from realtors, official records, and Finn.no (a Norwegian classified advertisement web-site) and combines such data with other information. Eiendomsverdi specializes in constructing automated valuation methods that deliver price assessments for commercial banks and realtors in real time. Commercial data are merged with official records and the resulting data set is a comprehensive register of publicly registered housing transactions in Norway, 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, sell price, and appraisal value 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. 67,746 individuals were observed to buy exactly twice.

3.4 Survey data

To understand how people perceive the role of the ask price, we were allowed to include our own questions in a survey of 2,500 customers of the largest Norwegian bank, DNB. These questions became part of a larger survey on the housing market conducted by DNB in collaboration with Ipsos. This larger survey is an on-going project and has been conducted on a quarterly basis since 2013. 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 purchase prices relative to the ask price, and how important people perceive the realtor to be for the sell price. The questions we added were 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, we let detailed results be reported in Appendix A.

4 Empirical approach

4.1 Empirical specification

We study how a strategic mark-down affects auction dynamics and auction outcomes. Our variables of interest are measures that characterize the auctions. Our notation uses h for houses (housing units) and t for time of sale. We let the notation $y_{h,t}$ represent a measure from the following list:

$$y_{h,t} = \left\{ No.Bidders_{h,t}, \frac{Opening\ bid_{h,t} - Appraisal_{h,t}}{Appraisal_{h,t}}, \right. \\ \left. \frac{Sell_{h,t} - Appraisal_{h,t}}{Appraisal_{h,t}}, \frac{Ask_{h,t} - Appraisal_{h,t}}{Appraisal_{h,t}} \right\}.$$

The empirical specification used to test how a strategic mark-down impacts these variables is given by:

$$y_{h,t} = \eta_h + \alpha_t + \zeta log(P^{App}_{h,t}) + \beta \text{Strategic mark-down}_{h,t} + Controls + \varepsilon_{h,t}, \qquad (6)$$

in which h indexes the unit that is sold at time t and α_t refers to year-by-month fixed effects. We include the appraisal value, $P^{App}_{h,t}$, to control for the price level of the unit h at time t in order to isolate the strategic mark-down effect from the price level. Our variable of interest, the strategic mark-down, is defined as $\text{Strategic mark-down}_{h,t} = \frac{-\left(Ask_{h,t} - Appraisal_{h,t}\right)}{Appraisal_{h,t}}$. We consider a sub-sample that consists of units that are transacted multiple times, which allows us to control for unit fixed effects, η_h. Additionally, we control for common debt, realtor fixed effects, and realtor-office fixed effects.

4.2 The appraisal value as a measure of expected sell price

We use the appraisal value as a benchmark to measure the market value of a unit. In this sub-section we explain why we choose the appraisal value as a gauge of market price and point of the qualities of appraisal value.

Sell-appraisal distribution

The sell-appraisal spread is relatively symmetrically distributed around zero, with a large mass at zero.[14] This pattern is consistent with the notion 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, a level of explanatory power that further bolster this claim.

Price growth and strategic mark-down

Since the appraisal value is set before the unit is listed for sale, one potential concern could be that there could be very few units with strategic mark-downs when house prices are increasing, simply because the ask price is set after the appraisal value. If the house price level increases substantially in the time period between the date of the appraisal value and the date of the ask price, it could be tempting for a seller to set the ask price above the appraisal value. Conversely, in a market with decreasing prices, the concern could be that ask prices tend be lie below the appraisal value, not because of a decision the seller deliberately makes, but because of market developments. Our data suggest that, if anything, the pattern is the opposite: more units are listed with strategic mark-downs in a rising market than in a falling market. The strategic mark-down appears to somewhat pro-cyclical, counter to the concern raised above. [15]

5 Empirical results

5.1 Baseline results

Table 4 shows our baseline results without unit-fixed effects.[16] All four specifications control for the appraisal value and common debt. In specification (I), we add year-by-month fixed effects. In the first column, we report results when the

[14]See Figure B.2 in Appendix B.

[15]See Figure B.3 in the Appendix B for details. The figure shows the fraction of units with a strategic mark-down (measured on the left y-axis) against the median house price growth (measured on the right y-axis).

[16]These specifications are confined to Oslo, Asker, Skedsmo, Fredrikstad, Bærum, Stavanger, Bergen and Lillehammer. The rest of Norway is excluded due to low transaction volumes.

dependent variable is the number of bidders. We see that using a strategic mark-down leads to more bidders, although the effect is small. In the second column, we estimate how the opening bid-appraisal spread is affected by using a strategic mark-down. The coefficient estimate is -0.957. The interpretation is that a one percentage point larger strategic mark-down is associated with a 0.96 percentage point reduction of the opening-bid-appraisal spread.[17] An ask price reduction is associated with almost a similar-sized reduction of the opening bid.

Table 3: Strategic mark-down coefficient for selected outcome variables across several specifications. Norway, 2007–2015

	Outcome variable:			
Model specification	No. bidders	Op.bid-App. spr.	Sell-App. spr.	Sell-Ask. spr.
(I): Year-by-month FE	0.004*	-0.957***	-0.768***	0.080***
	(0.002)	(0.008)	(0.008)	(0.008)
No. obs.	40,684	40,648	40,684	40,684
Adj. R^2	0.041	0.334	0.287	0.138
(II): (I) + Zip-code FE	-0.000	-0.953***	-0.779***	0.068***
	(0.002)	(0.008)	(0.008)	(0.008)
No. obs.	40,652	40,616	40,652	40,652
Adj. R^2	0.105	0.341	0.326	0.188
(III): (II) + Hedonics	0.002	-0.957***	-0.765***	0.080***
	(0.002)	(0.008)	(0.008)	(0.008)
No. obs.	39,672	39,637	39,672	39,672
Adj. R^2	0.118	0.347	0.333	0.196
(IV): (III) + Realtor FE	0.002	-0.960***	-0.760***	0.081***
	(0.002)	(0.008)	(0.008)	(0.008)
No. obs.	39,653	39,619	39,653	39,653
Adj. R^2	0.135	0.356	0.349	0.218

Notes: The table shows how different auction outcomes are affected by increasing the strategic mark-down (lowering the ask price relative to the appraisal value). The sample covers the period 2007–2015. 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. The sample is confined to Oslo, Asker, Skedsmo, Fredrikstad, Bærum, Stavanger, Bergen and Lillehammer. The rest of Norway is excluded due to low transaction volumes. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

The coefficient estimate of the sell-appraisal spread is -0.768 and the estimate is statistically significant. Nevertheless, the coefficient estimate of the sell-ask spread

[17] Or, since the spread is a fraction, a reduction of the ask-appraisal spread (the mark-down) of 0.01 is associated with a reduction in the opening bid-appraisal of 0.0096. To ease reading, we use the term a "percentage point" as a reference to a fractional change of 0.01.

is 0.080 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.

In specification (II), (III) and (IV), we sequentially add controls for zip-code FE (II), attributes of the unit (III)[18], and realtor and realtor-office fixed effects (IV). Results are robust across specifications.

5.2 Unobserved heterogeneity

Unobserved unit heterogeneity

Time-invariant unit characteristics:

In order to control for unobserved unit heterogeneity, we add unit fixed effects to our baseline model. In our data, there are 2,679 units that are sold at least twice, which limits the sample relative to the baseline results. Table 4 tabulates results based on estimating (6) for different outcome variables.

We find the coefficient on the strategic mark-down to be 0.014 when the dependent variable is the number of bidders. The interpretation uses the definition of the dependent variable given above, in which we measure the mark-down from the appraisal value. A lower ask price increases the mark-down. Thus, the positive sign means that a larger mark-down is associated with a higher number of bidders, i.e., all else being equal (ensured by the controls), a larger mark-down is associated with more bidders. In the third column, we estimate how the opening bid-appraisal spread is affected by using a strategic mark-down. The coefficient estimate is -0.958. The interpretation is that a one percentage point larger strategic mark-down is associated with a 0.96 percentage point reduction of the opening-bid-appraisal spread.

The coefficient estimate of the sell-appraisal spread is -0.904 and the estimate is statistically significant. The interpretation is that a one percentage point increase in the strategic mark-down is associated with a 0.9 percentage point reduction in the sell-appraisal spread. The coefficient estimate of the sell-ask spread is 0.107 and statistically significant. If this estimated coefficient had been zero, an increase in the mark-down, i.e. a reduction of the ask price, would not have been associated with a change in the sell-ask spread. Since the estimated coefficient is statistically significantly different from zero, an increase in the strategic mark-down is in fact associated with an 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

[18] We add the following attributes: the logarithm of the size, the square of the logarithm of the size, unit type, a lot size dummy if the lot is greater than 1000 square meters, construction period dummies, and dummies controlling for type of ownership.

the ask price positively affects the sell-ask spread, which, we argue, realtors use as a performance gauge when they recruit new clients.

The overall impression of these regressions is that we find statistically significant estimated coefficients and the explanatory power is high. For the sell-appraisal spread regression, the adjusted R^2 is 0.75, which is considerable when one takes into account that the variation in the appraisal value explains much of the variation in the sell price. Thus, this spread is a residual. Nevertheless, running a regression with this residual, the part of a sell price not explained by the appraisal value, yields results that explain a great deal of the residual variation.

Table 4: Strategic mark-down coefficient for selected outcome variables using unit fixed effects. Units sold at least twice. Norway, 2007–2015

	Outcome variable:			
	No. bidders	Op.bid-App. spr.	Sell-App. spr.	Sell-Ask. spr.
Strategic mark-down	0.014**	-0.958***	-0.904***	0.107***
	(0.005)	(0.024)	(0.026)	(0.026)
No. obs.	5,582	5,572	5,582	5,582
Adj. R^2	0.218	0.723	0.751	0.286
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 strategic mark-down (lowering the ask price 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 unobserved heterogeneity through regressions with 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. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

The key result is that the anchoring effect dominates the herding effect. Even if a strategic mark-down is associated with a higher number of bidders (herding), a strategic mark-down is associated with a lower opening bid (anchoring). Since the latter effect is stronger, the total effect is negative: a larger strategic mark-down is associated with a lower sell price as measured against a neutral value yardstick, i.e., a lower sell-appraisal spread.

Time-varying unit characteristics:

There may also be other forms of unobserved unit heterogeneity that could obfuscate our results. We have defined a strategic mark-down as an ask price that is set below the appraisal value. This choice of wording implicitly assumes that the observed difference between the ask price and the appraisal value is the result of strategic price-setting, not other causes. It is possible to raise the concern that, for some units, the appraisal value might be off the latent market value. Since the appraisal value involves an appraiser, who can make mistakes, some appraisal values might be set to high, others too low. The former may appear as a strategic mark-down even if the ask price simply 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 mark-ups.

A high appraisal value would be the result if there exist negative quality aspects that are not observed by the appraiser, but nevertheless are known to the seller and the realtor. One example could be a need for renovation that is not easily detected. The implication is a bias caused by unobserved unit heterogeneity. This unit heterogeneity is not permanent and thus cannot be dealt with using a unit-fixed effect set-up. Instead, this unobserved heterogeneity is time-varying. In order to investigate the possibility of renovation need, we have acquired a transaction data set of homes that have been renovated and in which we know the year of renovation.[19] To explore whether there is a difference in renovation frequency between the group of units that have a strategic mark-down 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 5. 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 subsequent to a sale.

[19]The data have been provided by the firm Eiendomsverdi AS.

Table 5: Renovation propensity in years around sale. Units with strategic mark-down versus units without strategic mark-down. t is the year in which the unit was sold. Norway, 2007–2015

	Dep. variable: Dummy variable for renovation				
	t-4	t-2	t	t+2	t+4
Strategic mark-down	0.078***	0.122***	0.218***	0.033***	0.025***
	(0.003)	(0.004)	(0.005)	(0.003)	(0.002)
No strategic mark-down	0.069***	0.113***	0.204***	0.047***	0.033***
	(0.004)	(0.005)	(0.006)	(0.003)	(0.002)
No. obs.	10,427	10,427	10,427	10,427	10,427
p(H_0: Disc. $\leq$ No disc.)	0.035	0.087	0.041	1.000	0.994

Notes: Data on renovation year was obtained from Eiendomsverdi. The table was generated the following way. In our first regression, we defined our dependent variable as unity if time of renovation was exactly equal to the year of sale and zero otherwise. We then regressed this outcome variable on a space consisting of two variables and no intercept: the first independent variable is unity if the sale involved a strategic mark-down and zero otherwise and the second independent variable is unity if the sale did not involve a strategic mark-down and zero if it did. This regression amounts to obtaining renovation frequencies for the two groups. We proceeded the same way for the other four years and we report the results in two columns to the left and the two columns to the right of the first regression results. The table also reports p-values from a test of equal renovation frequencies among units that use a strategic mark-down and units that do not use a strategic mark-down. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

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, a trait the seller might even be unaware of herself. Assume that there are 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 both to use a strategic mark-down and accept a low bid too soon. If so, the impatient seller would more often than the patient seller be involved in sales that have strategic mark-down and that are characterized by a low sell price compared to the appraisal value. This unobserved seller heterogeneity would bias our results towards magnifying the negative effect of a strategic mark-down on the sell price.

We attempt to deal with this possibility using a battery of tools. First, we investigate the distance between opening bid and accepted bid. Impatience would imply a lower distance since the impatient seller would tend to accept a bid before the auction process had exhausted all potential bids. Thus, a latent personality trait that implied both a strategic mark-down and a tendency of early acceptance of low bids would imply an association between a strategic mark-down and a reduced distance between opening bid and accepted bid. As shown in Table 1, we find no evidence of this. For the group with ask price below appraisal value, the spread between opening bid and sell price was -8.99 percent. For the group with ask price above or equal to appraisal value, the spread was -9.05 percent.

Second, it is reasonable to believe that impatience would affect time-on-market (TOM) so that impatience would lead to a lower TOM among units with strategic mark-downs. Generally, time-on-market is short in Norway and 90 percent of the units in our sample are sold within 100 days. This suggests that the incentive to sell fast may be less relevant in the context of the Norwegian housing market than in many other countries. We do, however, explore how a strategic mark-down affects the probability of fast sales and find no association between the use of a strategic mark-down and the probability of fast sales. A strategic mark-down could also be the result of the seller rationally lowering the ask price relative to the appraisal because he has information about the unit that is not observable to the realtor. If so, these units could also be harder to sell, leading to a higher TOM. There is a slight increase in the probability of slow sales for units with a strategic mark-down.[20]

We have also explored how the likelihood of expiration bids are affected by a strategic mark-down. For this purpose, we identify auctions in which at least one bid has expired before the unit is sold. In these auctions, the seller has decided to decline at least one bid, with the risk of not receiving more bids. We study auctions with expiration bids in which it takes at least 1 day, at least 3 days, at least 5 days and at least 7 days before the unit is eventually sold. There is no association between the probability of expiration bids and a strategic mark-down.[21]

As a final way of controlling for unobserved seller heterogeneity, we employ an instrumental variable approach. We instrument the mark-down variable with the median mark-down in the municipality in which the seller is selling his unit. This median is based on units sold within the same quarter.[22] Results from the

[20]To explore this, we identify units that are sold fast and slow relative to other units in the same municipality and within the same quarter. Fast sales are defined in two ways: units that sell faster than the 10^{th} and 25^{th} percentile of the TOM-distribution in the same municipality and quarter. We therefore also look at the link between the probability of slow sales and the use of a strategic mark-down. Slow sales are defined as units having a TOM longer than the 75^{th} and the 90^{th} percentile of the TOM-distribution in the same municipality and quarter. For both slow and fast sales, we follow units that are sold at least twice to control for unit fixed effects and estimate a set of logit models. Results are summarized in Table B.3 in Appendix B.

[21]Results are summarized in Table B.4 in Appendix B.

[22]To partially investigate the orthogonality condition, we regress the residuals from the baseline regressions (as reported in Table 3) on the proposed instrument. Results are recorded in Table

instrumental variable approach are reported in Table 6. First stage results (lower part of the table) suggest that the instrument is strongly correlated with the strategic-mark down, and all our results are maintained in this case (upper part of the table).

Table 6: Strategic mark-down coefficient for selected outcome variables. An instrumental variable approach. Units sold at least twice. Norway, 2007–2015

	Outcome variable:			
	No. bidders	Op. bid	Sell-App.	Sell-Ask.
Strategic mark-down	0.017	-0.847***	-0.894***	0.089
	(0.026)	(0.118)	(0.124)	(0.127)
No. obs.	5,582	5,572	5,582	5,582
Adj. R^2	-1.520	-0.511	-0.550	-1.513
Controls:				
Common debt	✓	✓	✓	✓
Appraisal	✓	✓	✓	✓
Realtor FE	✓	✓	✓	✓
Realtor office FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
First stage results:				
	Parsimonious	Fully specified		
Med. mark-down in mun.	1.009***	0.888***		
	(0.009)	(0.091)		
Adj. R^2	0.706	0.753		

Notes: The table shows how different auction outcomes are affected by increasing the strategic mark-down (lowering the ask relative to the appraisal value) when we consider an instrumental variable approach. We use the median mark-down in the municipality in which the unit is sold as an instrument. The median is calculated based on all transactions taking place in that municipality within the same sales-quarter. The sample covers the period 2007–2015. We consider only units that are sold at least twice, in order to control for unit fixed effects. In addition, we control for common debt, appraisal value, realtor fixed effects, realtor office fixed effects, and year-by-month fixed effects. The lower part of the table shows the first-stage results. The term "Parsimonious" refers to a regression in which the strategic mark-down is regressed on to the instrument only, whereas the term "Fully specified" refers the first-stage regression in a 2SLS. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

B.5 in Appendix B. There is no association between the residuals from the baseline regressions and the suggested instrument.

Compositional bias: Segmentation on price, size, TOM, house type and location

The summary statistics in Table 1 show that units listed with strategic mark-down tend to be smaller and have a higher appraisal value. Apartments are represented more often among the sample of units with strategic mark-down. Low ask price units are sold in the capital city of Oslo with higher frequency. We have also seen that there is an increased, though minor, probability of slow sales for units listed with a strategic mark-down. Finally, there are some differences between the selling process of co-ops and owner occupied units. Most importantly, co-ops have a clause that allows members of the co-op to enter into a bid and buy at the same price as the highest bid, after a given deadline. Then, the highest bidder will not be able to bid one more time, but actually loses the auction. Thus, in bidding for co-ops a bidder does not only compete with other bidders, but also with co-op members who can use the bid to acquire the unit. Thus, to prevent that, one must bid higher than the actual, observed competition.

We investigate the sensitivity of our results to these potential compositional biases. In particular, we re-run the fixed-effects model and test the effect of increasing the mark-down on different auction outcomes for units that have an appraisal value below the median in their municipality versus units that are priced above the median. We do a similar robustness test based on size-segmentation and TOM-segmentation.[23] Furthermore, we re-do all our calculations for 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 7.

[23] Since we follow repeat sales, we require that the unit belongs to the same category in all sales.

Table 7: Strategic mark-down coefficient for selected outcome variables. Segmentation on price, size, type, and location. Units sold at least twice. Norway, 2007–2015

		Outcome variable:			
	No. obs.	No. bidders	Op. bid	Sell-App.	Sell-Ask.
Baseline	5582	0.014**	-0.958***	-0.904***	0.107***
		(0.005)	(0.024)	(0.026)	(0.026)
Norway ex. Oslo	3823	0.009*	-0.960***	-0.916***	0.091***
		(0.005)	(0.026)	(0.028)	(0.028)
Houses	836	0.022	-0.830***	-0.732***	0.240*
		(0.023)	(0.176)	(0.137)	(0.142)
Owner occ.	3110	0.042***	-0.911***	-0.789***	0.232***
		(0.011)	(0.050)	(0.049)	(0.050)
App. $\leq$ med(App.)	3322	0.002	-0.963***	-0.945***	0.062*
		(0.007)	(0.031)	(0.033)	(0.033)
App. $>$ med(App.)	1374	0.032	-0.956***	-0.832***	0.159*
		(0.020)	(0.082)	(0.080)	(0.082)
Size $\leq$ med(Size)	3814	0.020*	-0.876***	-0.773***	0.266***
		(0.012)	(0.051)	(0.057)	(0.058)
Size $>$ med(Size)	1253	0.027	-0.761***	-0.797***	0.209*
		(0.019)	(0.127)	(0.105)	(0.107)
TOM $\leq$ med(TOM)	1220	0.087*	-0.879***	-0.425**	0.733***
		(0.052)	(0.208)	(0.215)	(0.220)
TOM $>$ med(TOM)	886	0.005	-1.006***	-0.980***	0.022
		(0.010)	(0.041)	(0.045)	(0.045)

Notes: The table shows how different auction outcomes are affected by increasing the strategic mark-down (lowering the ask relative to the appraisal value) for different sub-samples. The sub-samples cover the period 2007–2015. We consider only units that are sold at least twice, in order to control for unit fixed effects. In addition, we control for common debt, appraisal value, realtor fixed effects, realtor office fixed effects, and year-by-month fixed effects. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

6 Realtor incentives, performance types, and the use of strategic mark-downs

6.1 A model of realtor incentives

Realtors are assumed to maximize profits over two periods; the present and the future. Realtors compete over contracts and sellers screen realtors in order to find the best suited realtor to give advise on selling the unit. Realtors are one of two skill-types, θ, with either high performance-score (H) or low performance-score (L). 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 $P_{1,r}$ 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 $SA_{1,r} = \frac{P_{1,r}-A_{1,r}}{A_1}$ 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 the density $f(P_h)$, or the expected value of the density, $P_h^\star$ were known, the seller in the second period would use $P_h^\star$, to construct a first-period performance-metric of realtor r. This performance metric would be the spread, $SE_h = \frac{P_{h,1,r}-P_h^\star}{P_h^\star}$, and we denote it 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.[24] Both sellers and realtors know that it is not available.

While the density $f(P_h)$ and the sell-expected spread $\frac{P_{h,1,r}-P_h^\star}{P_h^\star}$ 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 realtor type, θ_r so that $P_{h,1,r} = \omega(A_{h,1,r}, \theta_r)$. We do not specify the function $\omega()$.

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 $\pi_2^\star = \max\ \pi_2(R(P_2(A_2, \theta)$. Inserting the solution into the present value formula reduces the two-period problem to a one-period

[24]Neither the appraisal value nor the ask price is part of the public record in the transaction registry, but the realtor retains appraisal value and the ask price for his own record. In trade practice the sell-ask spread has evolved as a performance metric.

maximization problem:

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

The realtor's profits from the first sale $\pi_1(P_1)$ is a monotonic function of revenue, which is a monotonic function of the sell price in the first period P_1.[25]

The second-period probability of obtaining a contract, q, depends on the sell-ask spread in the first period, so that $q = q(SA_1(P_1(A_1, \theta), A_1, \theta)$. Thus, the realtor knows that his advice on 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.

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

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

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

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

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 right-most factor is the change in the first-period sell price from a change in the first-period ask price. The middle factor is the change in the first-period revenue from the first-period sell price. The left-most factor is the change in first-period profits from a change in first-period revenue. The middle and left-most factors are positive. Our empirical results above suggest that the sign of the right-most 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 right-most factor is the change in the first-period sell price from a change in the first-period ask price. The middle factor is the change in the first-period sell-ask spread from a change in the first-period sell price. The left-most factor is the change in the second-period contract probability from a change in the first-period sell-ask spread. The middle and left-most factors are positive. Our empirical results suggest that the sign of the right-most factor is positive, so that the second term is also positive.

[25]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 pre-specified threshold are no longer allowed.

The third term is the effect on the probability of obtaining a second-period contract through two factors. The right factor is the change in the first-period sell-ask spread from a change in the first-period ask price. The left factor is the change in the probability from a change in the sell-ask spread. The right factor is negative and the left 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 aim is to estimate the net effect. Since the partial derivatives are functions of realtor type, we will also explore differences across realtors.

6.2 Empirical results on realtor behavior

What characterizes realtors who are involved in sales with strategic mark-downs?

Our results suggest that a strategic mark-down is associated with a lower sell price. Nevertheless, about 50 percent of the transactions are listed with a strategic mark-down. In this section, we explore the co-existence of these two findings. Our results indicate that a strategic mark-down 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 and seek to signal skills. 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. Survey results (see Figure A.1a in Appendix A) suggest that survey responders trust advice from the realtor when they are making decisions on the ask price. It is therefore plausible that sellers do what realtors suggest they do. Furthermore, as is shown in Figure A.1b, 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 use a strategic mark-down is related to realtor performance. In our first approach, we partition each realtor's sales into two parts by splitting sales for each year in two. This leaves us with two parts of observations for each realtor for each year y, denoted $AS_{r,y}$ and $BS_{r,y}$. We collect these parts by first collecting across years for each realtor, $AS_r = \cup_y AS_{r,y}$ and $BS_r = \cup_y AS_{r,y}$, then collect across realtors, $AS = \cup_r A_r$, and $BS = \cup_r B_r$. Within each part AS or BS, realtors are ranked according to how their median sell-appraisal spread scores relative to other realtors' score in their parts AS or BS. We rank using quintile groups. If the realtor belongs to the first quintile in both parts AS and BS, we characterize this realtor as having "Very low performance-score". If the realtor belongs to the highest quintile in both parts, he is characterized as having "Very high performance-score". By following this procedure, we classify realtors using five categories of realtor type θ. The set of realtor types, Θ, consist of the following types:

$$\Theta = \Big\{ \text{Very low performance-score, Low performance-score, Normal performance-score,} \\ \text{High performance-score, Very high performance-score} \Big\}$$

Realtors who do not consistently belong to the same quintile, i.e., type, across parts AS and BS are discarded.

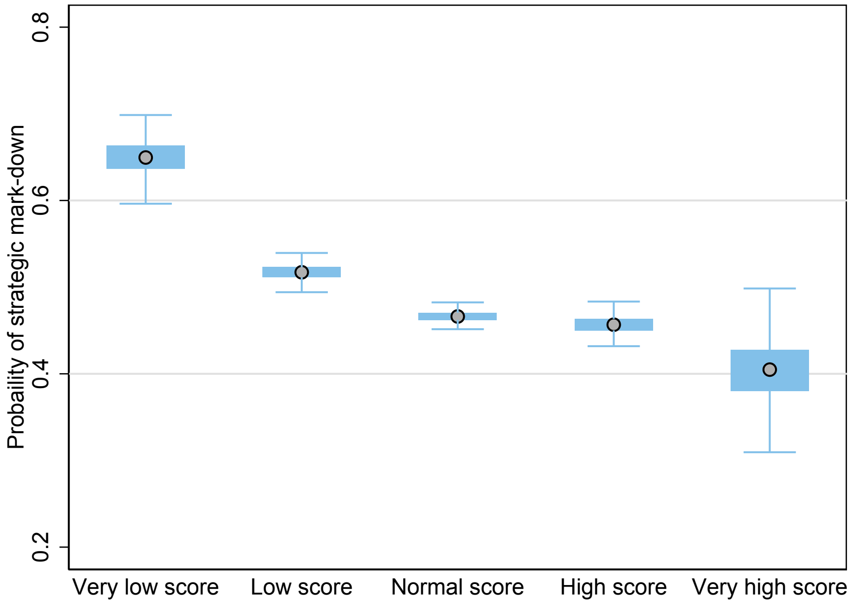
To explore whether realtor type matters for the likelihood of using a strategic mark-down, we estimate the following logit-specification:

$$P[Ask_{h,t,r} < Appraisal_{h,t,r}] = \frac{e^{\beta_{FE} + \gamma' \theta_{h,t,r}}}{1 + e^{\beta_{FE} + \gamma' \theta_{h,t,r}}}, \quad (11)$$

in which $\theta_{h,t,r}$ represents the realtor type θ of realtor r associated with the sale of house h at time t. The subscript FE is short notation for year-by-month, realtor office, and area fixed effects. γ is a five-by-one vector that contains the five coefficients representing the realtor type effects on the probability of using strategic ask price.

The partitioning into parts AS and BS is random. We repeat this exercise 1,000 times to perform a non-parametric Monte Carlo simulation of the estimation uncertainty. Box plots of the marginal effects for the likelihood of using a strategic ask price across the 1,000 draws are summarized for each of the five categories of realtor type in Figure 3. By visual inspection, we clearly detect a pattern. Realtors with very low performance-score are more likely to be associated with sales in which a strategic mark-down has been used. Realtors with very high performance-score tend to be associated with sales in which the ask price is equal to the appraisal value. In fact, the likelihood of using a strategic mark-down is monotonically decreasing in realtor performance.

Figure 3: Realtor score on performance and propensity to offer a strategic mark-down. Norway, 2007–2015



Notes: The figure shows box plots of the estimated probability of being involved in sales with a strategic mark-down across different realtor types. For each realtor and each year, we split the sample randomly in two. Then, samples are collected across years for each realtor. Within each of the two parts, realtors are ranked depending on their median sell-appraisal spread. We then categorize realtors based on quintile grouping. If the realtor belongs to the same quintile in both parts, he will be assigned a type. We run a logit regression in which the dependent variable is a binary variable, which is unity if the sale involved a strategic mark-down, and the independent variables are dummies for realtor's quintile category and fixed effect controls for year-month, realtor office, and area. We repeat this exercise 1,000 times to calculate bootstrapped confidence intervals.

Can realtors gain from advising the use of strategic mark-downs?

Our 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 a low ask price strategy is profit-maximizing. Essentially, the realtor can advise the seller either to use a strategic mark-down or not. 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 a random partitioning of each realtor r's annual sales into two parts, $AS_{r,t}$ and $BS_{r,t}$ and then characterize the performance. For this purpose, we consider two levels of performance, and say that a realtor is of the type "High performance-score"/ or "Low performance-score" when both his AS-sample and BS-sample median sell-ask spreads are above/below the median across all realtors in that year. We repeat this procedure 1,000 times in order to simulate the distribution of the estimates non-parametrically.

We then test whether a change (in the size) of the strategic mark-down between $t-2$ and $t-1$ has an impact on the change in revenue from $t-1$ to t. We study realtors who are classified with either High performance-score or Low performance-score in year $t-1$, and estimate the following equations for the two skill types:

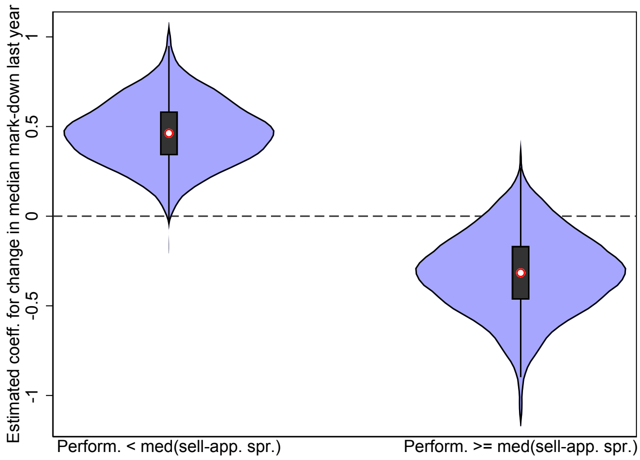
$$\Delta \text{Revenue}_{r,t}^{\theta} = \alpha^{\theta,m} + \beta_j^{\theta,m} + \eta_{l,t}^{\theta,m} + \gamma^{\theta,m} \Delta \text{Strategic mark-down}_{r,t-1}^{Median} \tag{12}$$

in which $\Theta = \{\text{High performance-score}, \text{Low performance-score}\}$. α is an intercept, β represents realtor office fixed effects, and η represents year-month-by-municipality fixed effects. The index r 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. The notation $\Delta\text{Revenue}_t$ refers as convention to the change in revenue from $t-1$ to t and $\Delta\text{Strategic mark-down}_{t-1}$ to the change in (the size of) strategic mark-downs between $t-2$ and $t-1$. The change in strategic mark-down is measured using median mark-downs for realtors. Our parameters of interest are $\gamma^{\theta,m}$, which measures the effect on revenue change from mark-down change. Figure 4 shows violin plots for estimated coefficients for the two groups. The violin plots show the full density based on all 1,000 draws.[26]

Our results suggest that a change in (the size of) strategic mark-down from $t-2$ to $t-1$ is not associated with any statistically significant effect on change in future revenue for High performance-score realtors since the right-most plot of the distribution of coefficient estimates clearly covers zero (dotted line). In contrast, for Low performance-score realtors there is an association between a change in (the size of) the strategic mark-down and an increase in next year revenues. The left-most plot of the distribution of coefficient estimates lies above zero at a high level of statistical significance. There is a difference between the two types of realtors, as measured by the performance metric sell-appraisal spread, to what extent changing the practice of strategic mark-downs has an effect on future revenue. The results are consistent with the notion that high performance-score realtors can focus attention on the sell price in order to increase the sell-ask spread while the low performance-score realtors focus attention on the ask price.

[26] Average coefficients and standard deviations based on the 1,000 draws are summarized in Table B.2 in Appendix B.

Figure 4: Realtor performance-score, use of strategic mark-down, and future revenue. Norway, 2007–2015



Notes: The figure shows a violin plot (the full distribution) for how a strategic mark-down in year t affects revenue change (lower panel) for two groups of realtors; those realtors who in year t achieve a sell-appraisal spread above the median and those realtors who got a sell-appraisal spread below the median. To rule out randomness, we split realtor-year observations randomly in two, and require a realtor 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.

6.3 Repeat-sellers: Do people learn?

Our results suggest that a strategic mark-down is a sub-optimal strategy for the seller. However, individual survey respondents report great trust in realtors, and certain types of realtors may gain from suggesting a strategic mark-down. These findings beg the question of whether sellers realize that strategic mark-downs are associated with low sell prices. Since typical holding times can be 7-10 years, 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 B.6 in Appendix B, we plot the frequency of sales with a strategic mark-down across different age groups. We observe that it is more common to use strategic mark-down among young sellers than among older sellers.

To the extent that using a strategic mark-down 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, i.e., we use repeat-seller, not repeat-sales, data.[27] We use these data to study whether previous experience with a strategic mark-down affects the strategy followed subsequently. Results are summarized in Table 8.

Table 8: Probability of strategic mark-down given past experience. Repeat-sellers, 2002-2018, owners with exactly 2 sales

	(I)	(II)
Intercept	0.010	0.502***
	(0.140)	(0.050)
SS	0.279***	0.108***
	(0.015)	(0.006)
SU	0.247***	0.096***
	(0.013)	(0.005)
NS	-0.053***	-0.017***
	(0.013)	(0.005)
Seller age	✓	✓
Month FE	✓	✓
Year FE	✓	✓
Unit FE	✓	✓
No. obs.	67,746	
Model	Probit†	OLS
AIC	90 511	
Adj. R^2		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 of the same unit are possible (e.g. married couples). 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 mark-down in the first sale (ask price below appraisal value) and was successful (sell price above appraisal value). SU means that the seller tried strategic mark-down 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: 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 do not use seller FE models. † We employ 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 estimate the for Model I all four coefficients for each of the 1,000 samples. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

The variable of interest is the probability of employing a strategic mark-down. The outcome variable is therefore a dummy taking the value one if the seller uses

[27] Eiendomsverdi accessed the historical register of owners for us.

a strategic mark-down 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 who have previously used a strategic mark-down (Strategic, S) and sellers who previously used an ask price equal to the appraisal value (Normal, N). We then partition each of these two groups into two sub-segments; those sellers who succeeded (S), i.e. they obtained a sell price in excess of the appraisal value, and those sellers who did not succeed (U). The four categories we consider are therefore: NU, NS, SS, and SU. We use NU as the reference category. 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).

The estimated coefficients for SS, SU, and NS are statistically significant. We observe that the probit-model (I) yields an estimated coefficient of 0.279 for the SS-variable (strategic mark-down was a success), which indicates that these sellers have an increased probability of repeating a strategic mark-down. The estimated coefficient for the NS (normal ask price was a success) variable is -0.053. The negative sign indicates a reduced probability of using a strategic mark-down in the subsequent sale. Taken together these two results indicate that sellers learn to continue with the successful strategy.

The estimated coefficient from the sellers who used a strategic mark-down, but was unsuccessful, is 0.247. This is a lower estimate than the SS-estimate, but it is positive. The interpretation is that unsuccessful sellers are less likely than successful sellers to continue with the strategic mark-down, but still more likely than sellers who succeeded with normal ask prices. This may indicate persistence in choice since sellers who perviously used a strategic mark-down (independent of the outcome) are more likely to employ a strategic mark-down in their next sale than those that previously did not use a strategic ask. This may be suggestive of differences in characteristics between sellers who employ strategic mark-down and those that do not. There seems to be some evidence of learning, albeit modest, among repeat-sellers.

7 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. The model we estimate bears close kinship with the hedonic model in Anundsen and Røed Larsen (2018). 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. A model contains no risk of a strategic element, which could be the case with the appraisal value to the extent that the appraiser is subject to a human element. We summarize results from the hedonic regression model in Table B.6 in Appendix B. Results when we re-estimate the regressions for auction outcomes on strategic mark-down when appraisal value is replaced by the model-predicted price are presented in Table B.7 in the same appendix. Results are robust to this alternative approach.

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 serves. To examine to what extent this possibility appears to affect our results, we also acquired transaction level data from Eiendomsverdi AS, consisting of transaction data from all realtor companies in Norway. Table B.8 summarizes the data in a check for balance. It is evident that the DNB Eiendom data is comparable to the full transaction level data. The main reason why we do not use the full transaction data set from Eiendomsverdi AS 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 and the anchoring effect.

Moreover, in the Eiendomsverdi-data we cannot control for realtor or realtor office fixed effects, so we cannot use Eiendomsverdi-data in investigating the effect realtors have on seller choices. 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 AS. None of our results are materially affected by choice of data source, and detailed results are reported in Table B.9 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 mark-down variable to change from year-to-year. Box-plots over years for each of the variables are plotted in Figure B.7 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 using a large or small mark-down, i.e., an ask price that is much lower or only marginally lower than the appraisal value. To explore this possibility, we partition our data into four discount categories; Very small mark-down (0-3%), Small mark-down (3-5%), Large mark-down (5-10%) and Very large mark-down (above 10%). We then interact the mark-down variable with dummies for each of the categories. Results are summarized in Figure B.8 in Appendix B. The pattern is intact.

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 mark-down that matters, but rather the nominal mark-down. 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. For example, the first interval spans an appraisal value of NOK 1.05 million, an appraisal value of NOK 2 million, and NOK 3.09 million. The next interval covers appraisal values of NOK 1.15 million, NOK 2.19 million, and NOK 3.1 million. Conditional on obtaining 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 price no lower than 100K below the lower end of the appraisal interval
3. Setting the ask price even lower than the preceding interval
4. Setting the ask price within the interval

The frequency of these strategies for different windows are shown in Figure B.9 in Appendix B. The most common strategy is to set the ask price 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 value, 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.10–B.12 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.

8 Conclusion

We study price-setting and incentives in the housing market and ask two related questions: How does using a strategic mark-down affect the sell price? Why do people choose different strategies? We construct a skeleton model that demonstrates that using a strategic mark-down generates two opposing effects, a positive herding effect and a negative anchoring effect. It is an empirical question which effect is stronger. If the answer to the question of how a strategic mark-down affects the sell price is that it reduces the sell price, one would expect that no sellers would use this strategy. Conversely, if the answer is that it increases the sell price, one would expect all sellers to use this strategy. Yet it turns out that about fifty percent of the sellers use the strategy while fifty percent of the sellers do not. This article first demonstrates that a strategic mark-down reduces the sell price, then goes on to try to explain why some sellers still use the strategy.

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 0.9 percent. The reason why is that the anchoring effect overwhelms the herding effect. The herding effect exists as a strategic mark-down is associated with more bidders in the auction. The anchoring effect materializes through a lower opening bid, and this effect is the strongest.

In our explanation of why some sellers still use this strategy, we construct a two-period model that shows that realtors face a trade-off between current profits and future profits. If the realtor advises on the use of a strategic mark-down in the current period, and the seller follows this advice, the result is a low sell price. The low sell price 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. It is, however, two ways to increase the sell-ask spread: One can increase the sell price or one can decrease the ask price. Of course, decreasing the ask price is self-defeating if such a decrease also leads to a similar decrease in the sell price. We find that a reduction in the ask price is indeed associated with a reduction in the sell price, but not a full 100 percent. A reduction in the ask price does increase the sell-ask spread. This is the key to understand how different realtor types are associated with different practices.

The type of advice a realtor gives appears to be related to the type of the realtor who is 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 low performance-score" to "Very high performance-score". There is a monotonically falling relationship between the frequency of being associated with a strategic mark-down and the performance metric. We then study why low performance-score realtors tend to be more frequently associated with strategic mark-down sales. Part of the explanation is found by examining what happens to realtors next period after having been connected to sales with mark-downs this period. There is an association between a change in strategic mark-down in the current period and a change in revenues in the future period for low-performing realtors. For high performance-score realtors, there is no association. Thus, it seems as if low performance-score realtors maximize inter-temporal profits by advising clients to use strategic mark-downs.

If a strategic mark-down benefits low performance-score 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 among sellers who have sold several times. 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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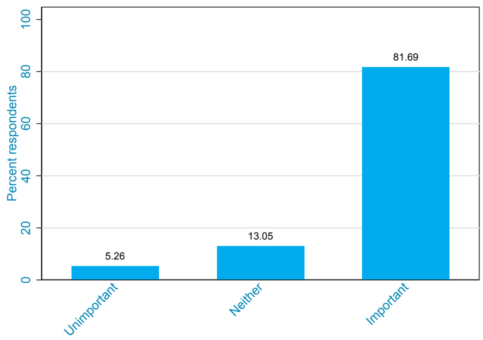
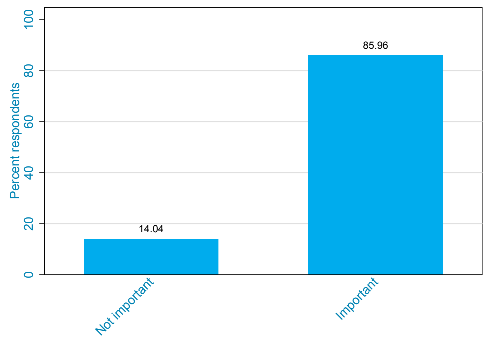
A Survey results

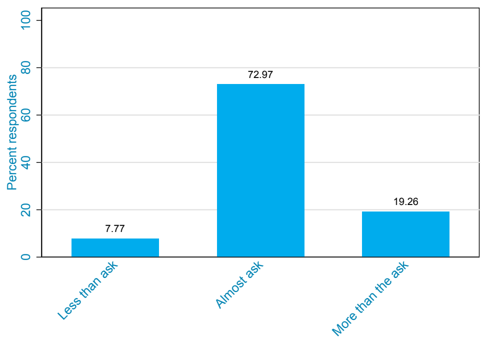
Figure A.1: Survey results, continues on next page



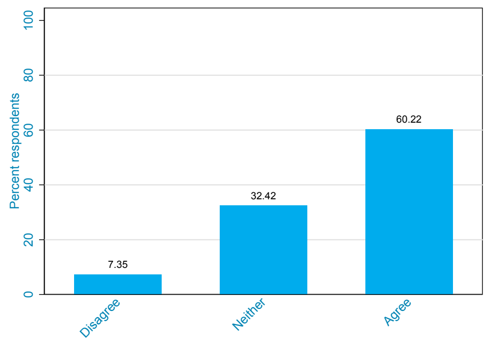
(a) How important is the realtor in deciding the ask price?



(b) How important is the realtor for the sell price?



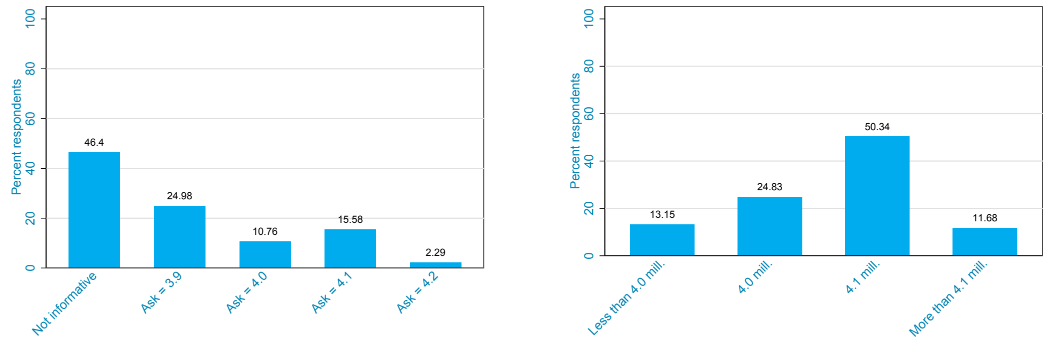
(c) What do you expect regarding the purchase price when you buy?



(d) Do you think a lower ask price attracts more bidders?

Notes: The histograms summarize results from a survey conducted by the firm Ipsos on 2,500 customers of the largest Norwegian bank, DNB. Our questions were included in a larger survey, which has been conducted on a quarterly basis since 2013. 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.

Figure A.1: Survey results, continued from previous page



(e) Four houses are similar. You can only visit one public showing. The appraisal is 4.1 in all cases. Which public showing do you attend?

(f) Your house is valued at 4.1 million. What ask price would you set?

Notes: The histograms summarize results from a survey conducted by the firm Ipsos on 2,500 customers of the largest Norwegian bank, DNB. Our questions were included in a larger survey, which has been conducted on a quarterly basis since 2013. 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.

B Additional results

Sell price, opening bid and number of bidders

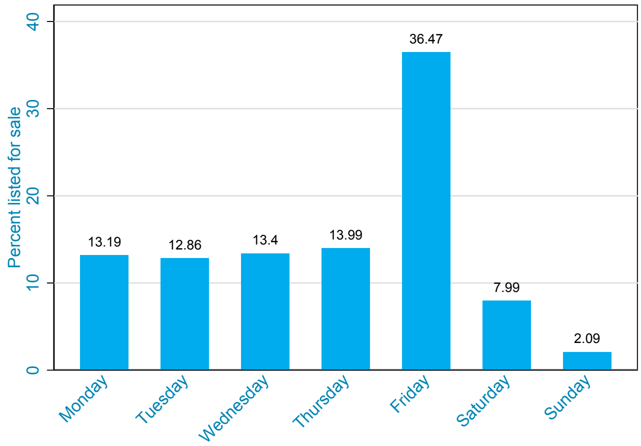
Table B.1: Sell-appraisal spread on number of bidders and opening bid-appraisal spread. Units sold at least twice. Norway, 2007–2015

	(I)	(II)	(III)
No. bidders	2.136***		3.037***
	(0.119)		(0.082)
Op. bid-App. spr.		0.606***	0.719***
		(0.018)	(0.014)
No. obs.	5,582	5,572	5,572
Adj. R^2	0.659	0.748	0.847
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 number of bidders and the distance between the opening bid and the appraisal value. The first two columns show results when only one of the variables are included, whereas the final column shows results when both variables are included. 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. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

Day of advertising

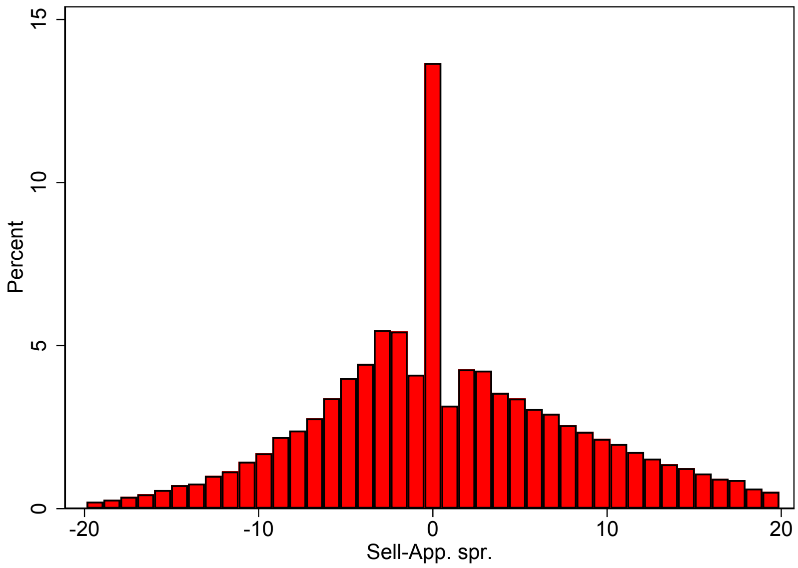
Figure B.1: Release day for online advertisement. All transactions. Norway, 2007-2015



Notes: The figure shows a histogram for the day of online advertisement of units listed for sale in Norway between 2007 and 2015.

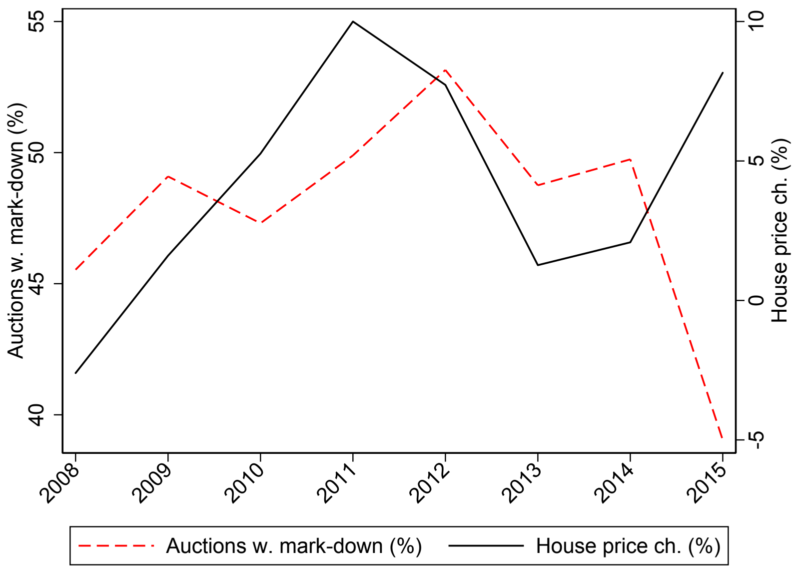
Appraisal validation

Figure B.2: Histogram of sell-appraisal spread. Norway, 2007-2015



Notes: 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.

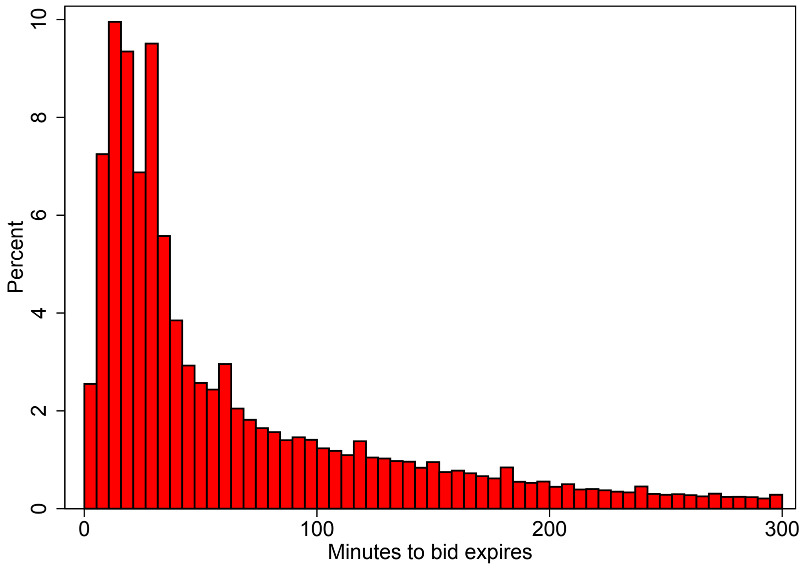
Figure B.3: Percent units advertised with strategic mark-down versus median house price change in percent. Norway, 2007–2015



Notes: The figure shows the percentage number of transactions in which a strategic mark-down (ask price lower than appraisal value) is used over time (left y-axis) and median house price growth (right y-axis) in Norway during the same period.

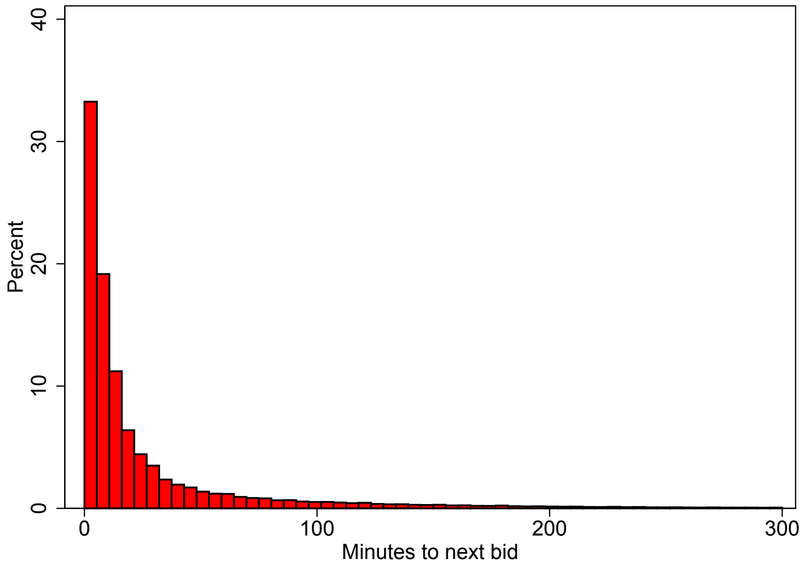
Bid expiration and time-to-next bid

Figure B.4: Histogram of minutes to bid expiry. Norway, 2007-2015



Notes: The figure shows a histogram of minutes to a bid expires for all bids recorded in the auction level data. The time-to-bid expiry is truncated at 6 hours to get a better visual impression of the distribution.

Figure B.5: Histogram of minutes to a new bid is placed. Norway, 2007-2015



Notes: The figure shows a histogram of minutes to a new bid is placed for all bids recorded in auctions with at least two bidders. The of minutes to a new bid is placed is truncated at 6 hours to get a better visual impression of the distribution.

Realtor quality and future market shares

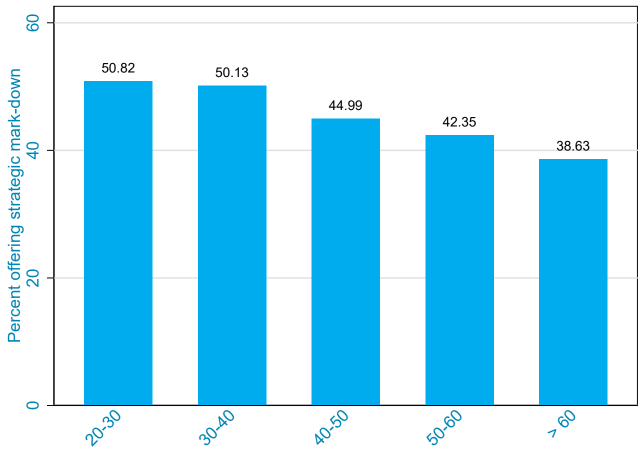
Table B.2: Change in median strategic mark-down (t-2 to t-1) among realtors and future revenue (t-1 to t). Segmentation on realtor performance. Norway, 2007–2015

	Dep. variable: Change in a realtor's revenue (in mill. USD) between $t-1$ and t	
	Realtors below median	Realtors above median
Δ Strategic mark-down$_{t-1}^{\text{Realtor median}}$	1.263***	-0.225
	(0.276)	(1.838)
Year FE	YES	YES
Local area FE	YES	YES
Realtor office FE	YES	YES

Notes: The table reports results from realtors whose performance is below median (measured in sell-appraisal spread) and from realtors whose performance is above median (measured in sell-appraisal spread). The results show how a change in the median strategic mark-down from year $t-2$ to $t-1$ (Δ Strategic mark-down$_{t-1}^{\text{Median}}$) affects revenue changes (in mill. USD) between $t-1$ and t. The interpretation of the coefficient is the association between a dollar change in revenue for a realtor this year and a change in the realtor's median mark-down by one percentage point last year. The sample covers realtor-year observations over the period 2007–2015 for realtors who sold at least 4 units in a given year. We use a specification with year fixed effects in order to control for the business cycle. In addition, we add fixed effects for the local area in which the realtor is selling most of his units, as well as realtor-office fixed effects. Reported results are those obtained from the Monte Carlo exercise used to construct Figure 4 in the paper. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

Strategic mark-down across age groups

Figure B.6: Frequency of strategic mark-down across age groups of sellers



Notes: The figure shows the frequency at which different age groups of sellers offer an ask price that is below the appraisal price. We do not include sellers younger than 20 years of age. 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 of the same unit are possible (e.g. married couples). The number of owners observed is 632,755.

Strategic mark-down, time-one-market and expiration bids

Table B.3: Strategic mark-down and slow versus fast sales. Units sold at least twice. 2007–2015

	Dep. variable: Dummy variable equal to one if the condition in the column in satisfied. Zero otherwise			
	Slow sales		Fast sales	
	TOM < p10(TOM)	TOM < p25(TOM)	TOM > p75(TOM)	TOM > p90(TOM)
Strategic mark-down	0.009	0.002	0.073***	0.101***
	(0.015)	(0.011)	(0.013)	(0.020)
No. obs.	836	1925	1889	766
Pseudo R^2	0.0151	0.0350	0.0508	0.0877
Controls:				
Common debt	✓	✓	✓	✓
Appraisal	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓

Notes: The table shows how a strategic mark-down affects the probability of fast and slow sales. Fast sales are measured in two ways: TOM less than the 10th and 25th percentile in the municipality (the left-most two columns). Slow sales are measured in two ways: TOM greater than the 75th and 90th percentile in the municipality (the right-most two columns). The sample covers the period 2007–2015. We consider only units that are sold at least twice, in order to control for unit fixed effects. In addition, we control for common debt, appraisal value, and year fixed effects. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

Table B.4: Expiration bids and strategic mark-down. Units sold at least twice. 2007–2015

	Dep. variable: Dummy variable equal to one if the condition in the column in satisfied. Zero otherwise			
	Bid exp. >= 1 day	Bid exp. >= 3 days	Bid exp. >= 5 days	Bid exp. >= 7 days
Strategic mark-down	0.003	0.005	0.008	0.009
	(0.006)	(0.011)	(0.011)	(0.011)
No. obs.	2655	2165	1969	1852
Pseudo R^2	0.0667	0.0424	0.0381	0.0370
Controls:				
Common debt	✓	✓	✓	✓
Appraisal	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓

Notes: The table shows how a strategic mark-down affects the probability of observing expiration bids. An expiration bid is defined as a bid that expires before another bid is accepted, i.e. the seller decided to decline (or not accept within the bid's duration) at least one bid in the auction, with the risk of not receiving more bids. We look at cases in which it takes at least 1 day, at least 3 days, at least 5 days and at least 7 days before a new bid is accepted. The sample covers the period 2007–2015. We consider only units that are sold at least twice, in order to control for unit fixed effects. In addition, we control for common debt, appraisal value, and year fixed effects. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

An instrumental variable approach

Table B.5: Association between residuals from baseline regression and the instrument. Norway, 2007–2015

	No. bidders	Op.bid-App. spr.	Sell-App. spr.	Sell-Ask. spr.
Instrument	0.003	0.103	0.009	-0.017
	(0.024)	(0.106)	(0.113)	(0.116)
No. obs.	5,582	5,572	5,582	5,582
Adj. R^2	0.516	0.116	0.546	0.539
Controls:				
Common debt	✓	✓	✓	✓
Appraisal	✓	✓	✓	✓
Realtor FE	✓	✓	✓	✓
Realtor office FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓

Notes: The table shows results from a regression of the residuals from the baseline regressions (as reported in Table 3) on the proposed instrument. The instrument is the median mark-down in the municipality in which the unit is sold. The median is calculated based on all transactions taking place in that municipality within the same sales-quarter. The sample covers the period 2007–2015. We consider only units that are sold at least twice, in order to control for unit fixed effects. In addition, we control for common debt, appraisal value, realtor fixed effects, realtor office fixed effects, and year-by-month fixed effects. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level. The adjusted R-square is high in three regressions, but that is not due to the instrument, but control variables. The instrument coefficient is statistically insignificant.

Results from estimated hedonic model

Table B.6: Selected results from the estimated hedonic model used to construct predicted prices. Norway, 2007–2015.

Independent variable:	log(Sell price)
Lot size > 1000sqm	3.054***
	(0.703)
Log(size)	-1415.719***
	(46.103)
$(Log(size))^2$	115.047***
	(3.158)
Log(size)× Apartment	75.010
	(59.207)
$(Log(size))^2$× Apartment	4.096
	(4.249)
Log(size)× Oslo	-216.495***
	(10.069)
$(Log(size))^2$× Oslo	29.213***
	(0.795)
No. obs.	113,769
Adj. R^2	0.800
Controls:	
Year-by-month FE	✓
Zip-code FE	✓
House type FE	✓
Contr. per. FE	✓

Notes: The table shows estimation results for the hedonic model used to construct the predicted prices used in the robustness exercise reported in Table B.7. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

Table B.7: Hedonic mark-down and auction dynamics. Using hedonic model to estimate market valuation instead of appraisal value. Units sold at least twice. Norway, 2007–2015

	No. bidders	Op.bid-Pred. spr.	Sell-Pred. spr.	Sell-Pred. spr.
Hedonic mark-down	-0.000	-0.964***	-0.986***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
No. obs.	7,951	7,937	7,951	7,951
Adj. R^2	0.194	1.000	1.000	0.272
Controls:				
Common debt	✓	✓	✓	✓
Appraisal	✓	✓	✓	✓
Realtor FE	✓	✓	✓	✓
Realtor office FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓

Notes: The table shows how different auction outcomes are affected by increasing the hedonic mark-down (lowering the ask relative to the predicted price obtained from the hedonic regression model reported in Table B.6). The sample covers the period 2007–2015. We consider only units that are sold at least twice, in order to control for unit fixed effects. In addition, we control for common debt, predicted price, realtor fixed effects, realtor office fixed effects, and year-by-month fixed effects. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

Robustness to using transaction-level data for all real estate companies

Table B.8: Summary statistics for transaction-level data for all real estate companies. Segmentation on ask price-appraisal value differential. Norway, 2007–2015

	Ask price < Appraisal value		Ask price ≥ Appraisal value	
Variable	Mean	Std.	Mean	Std.
Sell (in 1,000 USD)	428.4	214.3	416.71	229.6
Ask (in 1,000 USD)	415.66	210.83	405.97	222.64
Appraisal (in 1,000 USD)	430.75	218.1	404.94	222.63
Square footage	1011.69	513.81	1093.06	521.7
Strategic mark-down (in %)	3.57	3.91	-.35	3.89
Sell-App. spr. (in %)	-.14	9.54	3.11	9.42
Sell-Ask spr. (in %)	3.52	8.74	2.76	8.82
Perc. owner-occupied	63.13		67.3	
Perc. apartment	64.33		53.36	
Perc. Oslo	40.52		29.78	
No. auctions	153,719		168,735	

Notes: The table shows summary statistics for the transaction-level data for all real estate companies over the period 2007–2015. We distinguish between units with a strategic mark-down (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 $USD/NOK = 0.1639$. The summary statistics from this data set can be compared to those for the auction-level data reported in Table 1.

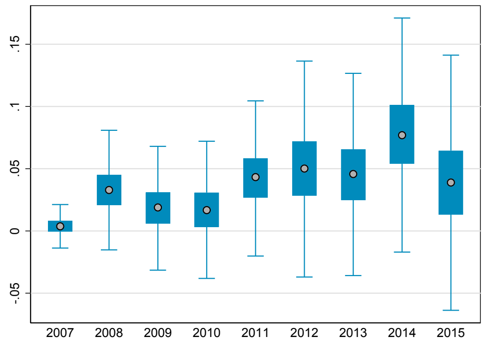
Table B.9: Strategic mark-down and spreads. Transaction-level data for all real estate companies. Norway, 2007–2015

	Sell-App. spr.	Sell-Ask. spr.
Strategic mark-down	-0.670***	0.226***
	(0.005)	(0.005)
No. obs.	174,834	174,834
Adj. R^2	0.336	0.240
Controls:		
Common debt	✓	✓
Appraisal	✓	✓
Time FE	✓	✓
Unit FE	✓	✓

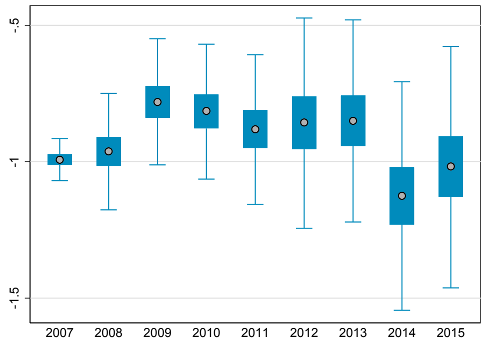
Notes: The table shows how different auction outcomes are affected by increasing the strategic mark-down (lowering the ask relative to the appraisal value) when we consider transaction-level data for all real estate agencies. This data set does not include information on the bidding-process, which is why the analysis is confined to the sell-appraisal spread and the sell-ask spread. 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 and year-by-month fixed effects. This data set does not include information on realtor-id or realtor office. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

Variations over the housing cycle. Norway, 2007–2015

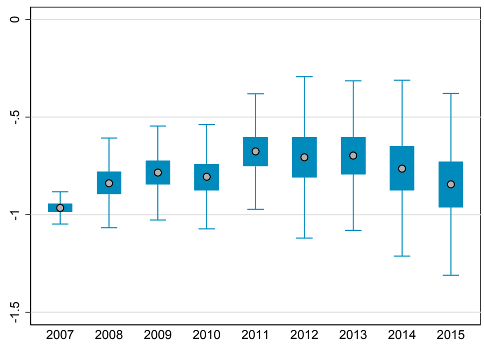
Figure B.7: Time-variation in the effect of the strategic mark-down on auction variables.



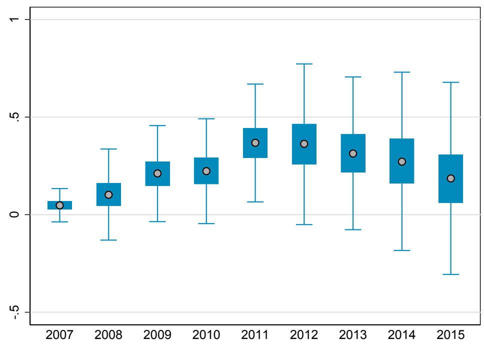
(a) No. bidders



(b) Op. bid-App. spr.



(c) Sell-App. spr.

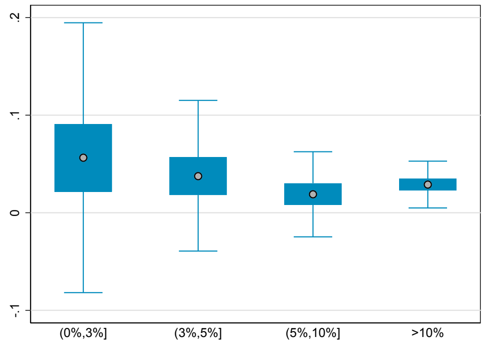


(d) Sell-Ask spr.

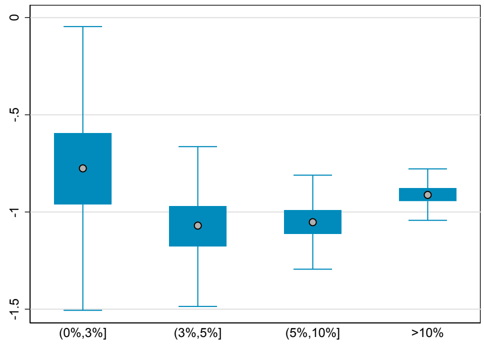
Notes: The figure shows year-specific effects of a strategic mark-down on different auction variables. Results are obtained by estimating the baseline regression models in eq. 6 year-by-year.

Non-linearities

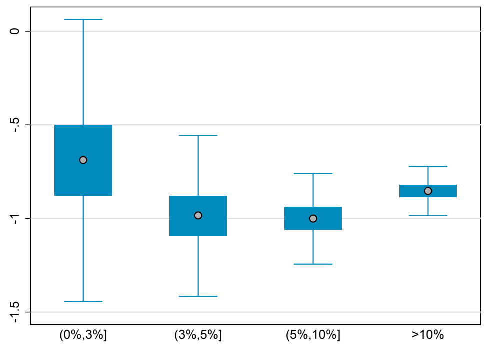
Figure B.8: Non-linear effects of strategic mark-down on auction variables. Norway, 2007–2015



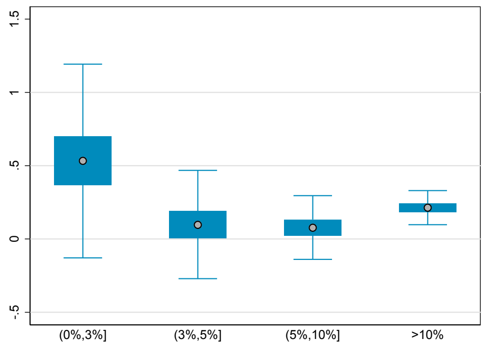
(a) No. bidders



(b) Op. bid-App. spr.



(c) Sell-App. spr.

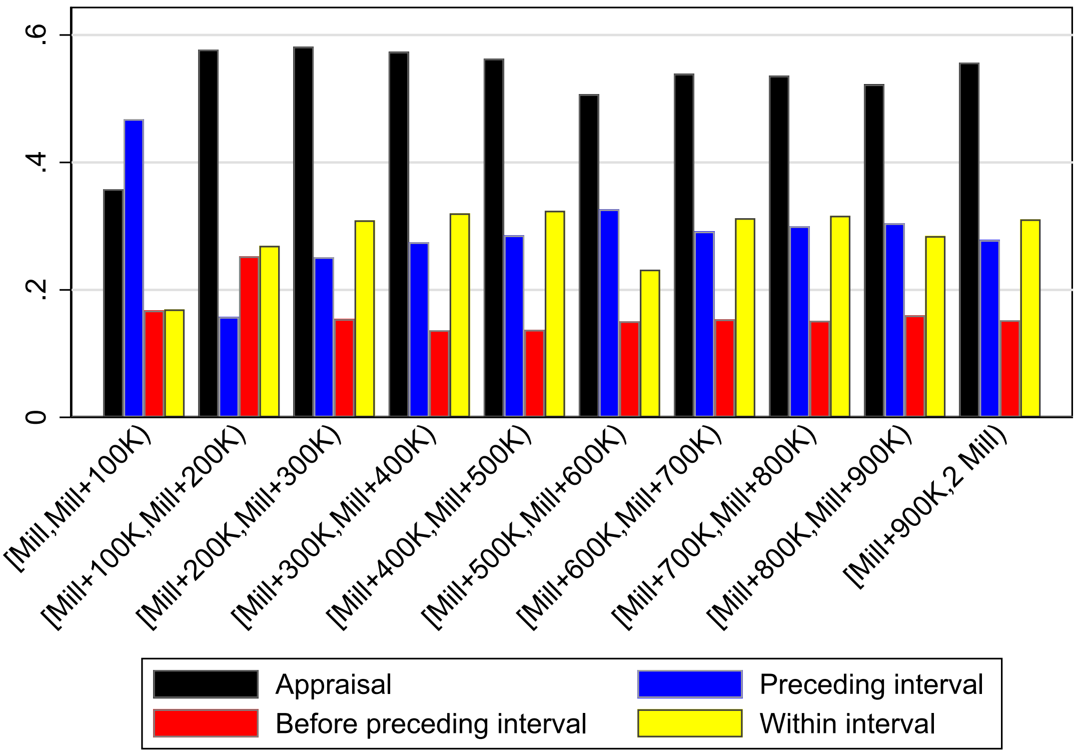


(d) Sell-Ask spr.

Notes: The figure shows effects of a strategic mark-down on different auction variables for different mark-down groups, categorized into different mark-down bins. Results are obtained by estimating a modified version of the baseline regression models in eq. 6 year-by-year. The modification is that the mark-down variable is interacted with dummy variables for each of the four groups.

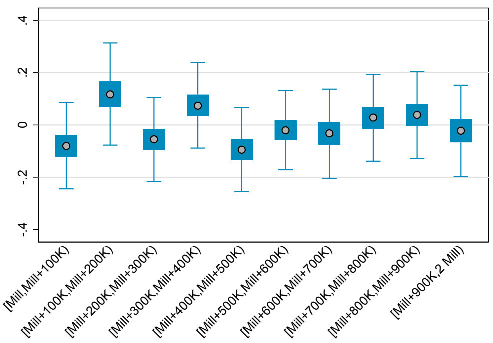
Different pricing strategies

Figure B.9: Frequency of different strategies. Norway, 2007–2015

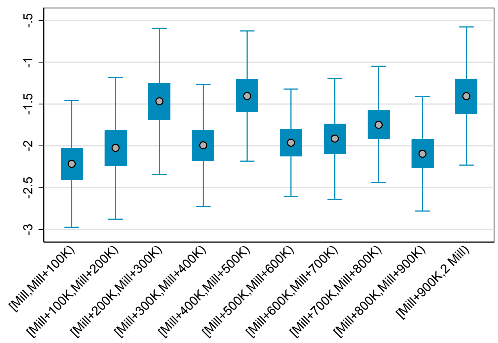


Notes: The histogram shows the frequency of different strategies for setting the ask price across the nominal price-spectrum. We study intervals of the appraisal value in NOK 100 thousands, in which all million-NOKs are converted to a round million. For example, the first interval (Mill, Mill + 100K) spans an appraisal value of NOK 1.05 million, an appraisal value of NOK 2 million, as well as NOK 3.09 million, etc, because they all lie within the round million and the round million plus 0.1 million. The next interval (Mill + 100K, Mill + 200K) covers an appraisal value 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. The histogram shows the frequency of four different strategies for the different intervals: setting the ask price equal to the appraisal value (black), setting the ask price so that one targets the preceding interval in the price-spectrum (blue), setting the ask price even lower than the preceding interval in the price-spectrum (red), or setting the ask price within the interval and different from the appraisal value (yellow).

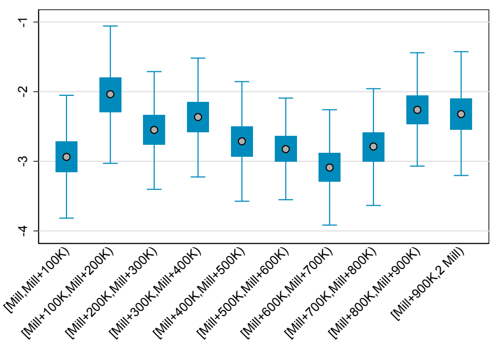
Figure B.10: Setting the ask price so that one targets the preceding interval of the appraisal value in the nominal price-spectrum. Effects relative to asking for the appraisal value. Norway, 2007–2015



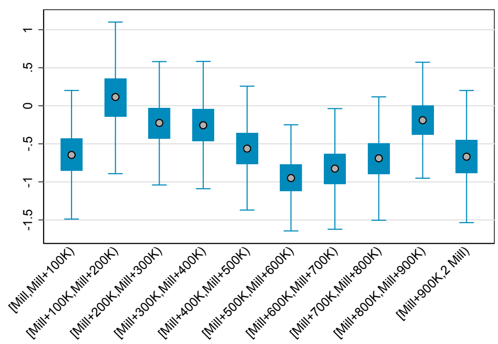
(a) No. bidders



(b) Op. bid-App. spr.



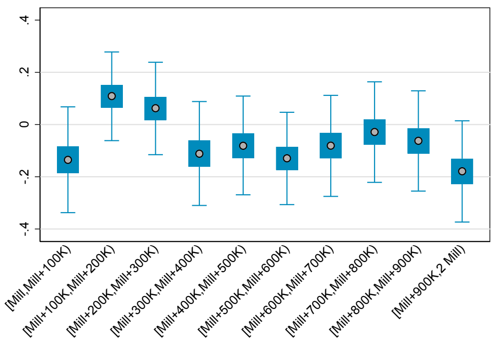
(c) Sell-App. spr.



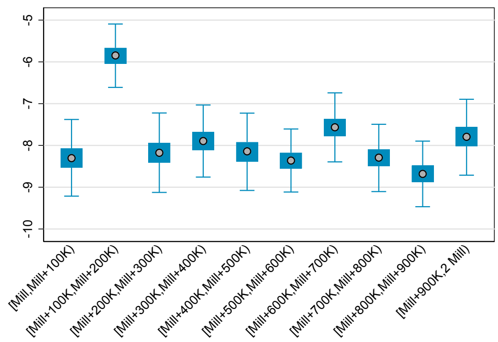
(d) Sell-Ask spr.

Notes: The figure show the effect of a ask price strategy that entails setting the ask so that one targets the preceding interval in the price-spectrum (ref. the blue bar in Figure B.9). Results are displayed for intervals of the appraisal value in NOK 100 thousands, in which all million-NOKs are converted to a round million. Thus, the first interval (Mill, Mill + 100K) 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 (Mill 0 100K, Mill + 200K) covers appraisal values of NOK 1.15 million, an appraisal value of NOK 2.19 million, as well as NOK 3.1 million, etc.

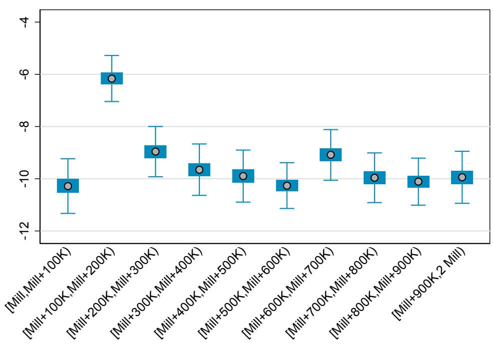
Figure B.11: Setting the ask so that one targets a nominal ask price lower than preceding the interval of the appraisal value in the nominal price-spectrum. Effects relative to ask price for appraisal. Norway, 2007–2015



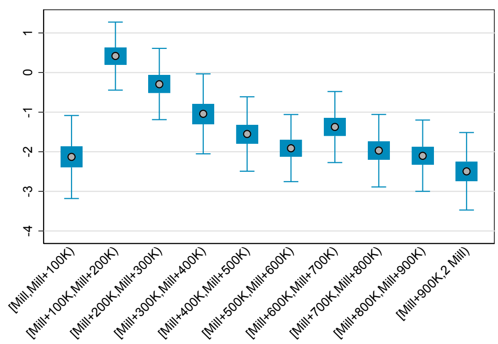
(a) No. bidders



(b) Op. bid-App. spr.



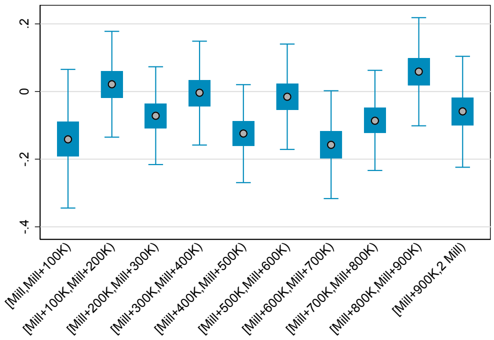
(c) Sell-App. spr



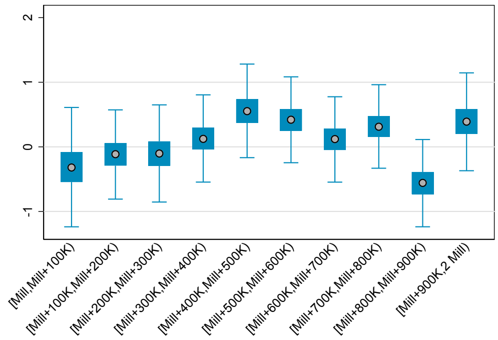
(d) Sell-Ask spr.

Notes: The figure show the effect of a ask price strategy that entails setting the ask price so that one targets a nominal ask price lower than the preceding interval in the price-spectrum (ref. the red bar in Figure B.9). Results are displayed for intervals of the appraisal value in NOK 100 thousands, in which all million-NOKs are converted to a round million. Thus, the first interval (Mill, Mill + 100K) 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 (Mill 0 100K, Mill + 200K) covers appraisal values of NOK 1.15 million, an appraisal value of NOK 2.19 million, as well as NOK 3.1 million, etc.

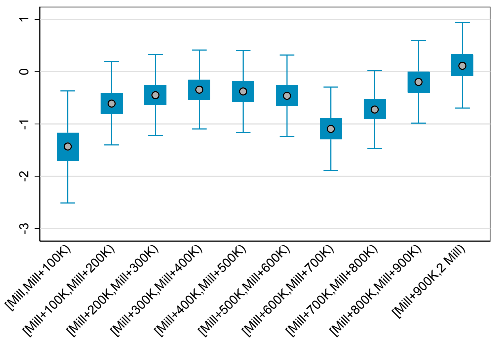
Figure B.12: Setting the ask so that one targets a nominal ask price within the interval of the appraisal value in the nominal price-spectrum. Effects relative to ask price for appraisal. Norway, 2007–2015



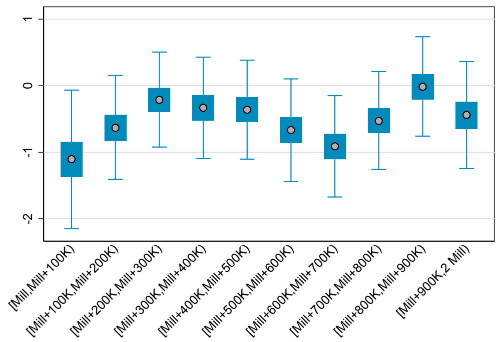
(a) No. bidders



(b) Op. bid-App. spr.



(c) Sell-App. spr



(d) Sell-Ask spr.

Notes: The figure show the effect of a ask price strategy that entails setting the ask price so that one targets a nominal ask within the interval of the appraisal value in the nominal price-spectrum (ref. the yellow bar in Figure B.9). Results are displayed for intervals of the appraisal value in NOK 100 thousands, in which all million-NOKs are converted to a round million. Thus, the first interval (Mill, Mill + 100K) 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 (Mill 0 100K, Mill + 200K) covers appraisal values of NOK 1.15 million, an appraisal value of NOK 2.19 million, as well as NOK 3.1 million, etc.

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