Strategic price-setting and incentives in the housing market*

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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 data and construct a performance measure for realtors. Using this measure, 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.

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. Despite intense scrutiny, many aspects of the price setting process are not yet fully understood. As digital market places expand, and auctions become more frequent, there is growing interest in how sellers can use ask prices as signals that affect outcomes. Lower ask prices might attract more bidders, but also lower the expectation of what bid wins the auction. Higher ask prices could scare away potential buyers, but at the same time anchor the expectation of the winning bid at a higher level. The role of the ask price is perhaps especially interesting when it is posted side-by-side a value estimate, such as an appraisal value from an expert or an estimate from an automatic valuation method, because then observers may use this information to form opinions on economic gains of participating in the auction. This article studies a universal problem, how to set an ask price, in the particular setting of auctions of Norwegian houses. We seek to investigate price setting by asking two concrete questions: How does setting a low ask price affect the sell price of a unit? Why do sellers choose different strategies when they set the ask price?

The short answer is that using a strategic mark-down, i.e. setting an ask price below a market estimate, reduces the sell price. This finding is based on analyzing data on repeat sales and repeat realtors that allow us to exploit observed variation and control for unobserved heterogeneity in units and realtors, while also controlling for the business cycle, geographical factors, and seller heterogeneity. Different strategies are associated with different realtors. 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 greater extent than high performance score realtors. We also show that among low performance score realtors, those who increase their mark-down tendencies are associated with an increase in revenues in the following year. There is no such effect among high performance score realtors.

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. A signalling structure emerges both when there is competition among sellers over prospective buyers and when there is competition among realtors over prospective sellers. For a seller, the ask price is a powerful signal (Han and Strange, 2015; Haurin et al., 2013; Herrin et al., 2004; Horowitz, 1992; Taylor, 1999). For a realtor, past performance is a signal of competence. Realtors thus seek to show sellers that they are able to achieve a high sell price, compared to a yardstick. We show that since realtors use the sell-ask spread as a marketing tool 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.

It is important for the seller that the ask price is set at the "correct" level. In order to get it right, the seller consults 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 when screening realtors. This means that advising on the right ask price will be a critical task for the realtor, as the spread between the sell price and the ask price will impact the recruitment of future clients. Both the seller and the realtor thus need to set the right ask price, but they have different objectives. The seller wants a high sell price. The realtor wants a high sell-ask spread for future marketing and a quick sale in order to minimize effort.

While the contribution of this paper is empirical, we start 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 in turn 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. Which effect is greater is an empirical question.

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-authorized appraiser, who physically inspects the unit, writes a technical report on the condition of the unit, and estimates its market value.[1] In contrast to the situation in other countries, the appraisal value has no bearing on the mortgage a prospective buyer is granted, and it is therefore not binding for home buyers who finance their property purchase through a bank. In Norway, the mortgages banks grant buyers depend upon the buyers' financial situations, not the units they contemplate buying. In fact, a bank often grants a prospective buyer a general mortgage certificate, i.e. a promise to lend, before the buyer starts the housing search, so that the buyer is aware of the upper limit of his potential bidding. Thus, appraisal value can therefore be considered as exogenous and highly useful as a gauge of market value. We examine the validity of the appraisal value using a battery of techniques, and it appears to be an unbiased estimator of sell price and its value does not systematically vary with realtors.

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 the practice of

[1]This was the practice in the period that our data set covers. Recently, the appraiser does not offer a market value estimate. After 2016, the assessment of market value is done by the realtor.

using a strategic mark-down as setting the ask price below the appraisal value. We use several tools in order to control for unobserved heterogeneity. We follow units that are sold at least twice and include unit fixed effects in our regressions. We follow realtors over time, which means that our regressions include realtor and realtor-office fixed effects. We also employ an instrumental variable approach to control for unobservable seller type. As an instrument, we use the fraction of units that are listed with a mark-down within the same zip-code and quarter. Our results show that the anchoring effect is considerable. In fact, an ask price that is 1 percent below the appraisal value tends to result in a sell price that is 0.9 percent lower than the counterfactual sell price that would have been achieved without the strategic mark-down. Strategic mark-downs do not appear to decrease the time-on-market substantially nor increase the sale probability substantially. We do find a herding effect, but this effect is dominated by the anchoring effect.

In order to understand why so many sellers set lower ask prices when this does not result in higher sell prices nor speedier sales, 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 in part, 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 realtors to advise sellers to set a high or low ask price and demonstrate that the choice depends on the realtor's skills.

The contribution of this paper is two-fold. First, we examine a unique data set on bidding activity in the housing market in relation to price setting and incentives, which is relevant to results in the literature on signalling and agency. Second, we explore in detail, 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.

Our analyses are based on a combination of Norwegian data sets. The main data set contains a complete log of all bids in all auctions from DNB Eiendom – one of the largest realtor companies in Norway. This data set includes information on unit, bidder and realtor identifiers across auctions. The data include about 120,000 auctions and over 750,000 bids during the period 2007–2015. We have information on every single bid, including the time when the bid was placed (to the minute), expiration of the bid (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 not only let us study how the ask price affects bidding behavior in a given auction, but they also permit us to follow repeat sales of the same housing unit. We can measure the performance of individual realtors across auctions. We also access information on units that were put up for sale in order to find out whether or not these units actually were sold. Finally, we were given the opportunity to attach our questions to an omnibus survey of households undertaken by Norway's largest bank, DNB. The main reason we collect these survey data is to examine the responses of buyers and sellers when questioned about the role of the ask price in housing auctions. Their answers shed light on the results from the bidding data, and 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 collected systematically for a reasonably long period. Second, the institutional setting of the Norwegian housing market makes it highly suitable for studying the effect of strategic mark-downs, since sales are organized through ascending-bid auctions. A typical sale follows a procedure that simplifies ex post inspection. A seller advertises a unit for sale online, which leaves an electronic record of the advertising date, ask price, and appraisal value. The advertisement contains a date for an open house. Interested parties inspect the unit at the open house, and this interest is recorded. All bids are legally binding, as are acceptances of bids. Thus, transfer of ownership is essentially locked in once the seller accepts a bid. The bidding activity takes place on digital platforms, which in turn implies that the bids are collected in data sets.

We perform several robustness checks and tests for alternative explanations for setting strategic mark-downs. It is fathomable that sellers also aim to increase the probability of sale. Most units are, however, transacted within 100 days in Norway. This means that the incentive of a quick sale may be less relevant in Norway than in other countries with longer TOMs. While Guren (2018) reports a base probability of sale in the U.S. within 13 weeks of 0.48, in Norway it ranges between 0.83 and 0.94. When we access a data set that consists of all units put up for sale in a year, i.e. both units that were sold and units that were not sold, and investigate which units have been sold or not long after a given period of time, we detect only small differences between the sale frequencies of units with strategic mark-downs compared to units without strategic mark-downs. This corroborates the findings in Andersen et al. (2019) for Denmark, who show that setting the ask price below the estimated market value from a hedonic model has a negligible impact on sale probability.

Second, within the set of mark-down strategies in the housing market, one type of strategy has received attention, the one exploiting the left-digit bias (Repetto and Solis, 2020). This strategy entails setting the ask price just below a round million. To study this particular strategy, we follow the approach in Repetto and Solis, 2020, and extend it by controlling for the appraisal value. We find that when unobserved heterogeneity is taken into account, the left-digit bias effect is reduced.

Third, we test whether our results are robust to segmentation on size, price, unit type, TOM, and location, and find that they are. Fourth, we show that an instrumental variable approach that handles potential self-selection by, and unobserved heterogeneity among, sellers yields similar results as our baseline approach. Fifth, we estimate a hedonic model in order to gauge the market value of each unit in the data set as an alternative way of measuring the ex ante market value. The results are robust to this change of approach. Sixth, the company Eiendomsverdi holds transaction-level data for all sales handled by every real estate agency in Norway. 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. Seventh, we test for possible time variation by redoing our analysis on a year-by-year basis. Our findings are robust to yearly segmentations. Eighth, potential non-linear effects of strategic mark-downs could arise if larger mark-downs drive the results. We do not find evidence of this. Finally, while less than four percent of the units in our sample are listed with an ask price above the appraisal value, we look into potential differential effects of using a mark-down versus a mark-up strategy. Effects on sell prices are symmetric, but we show that a mark-up strategy entails a lower sale probability – a finding that parallels Guren (2018) and Andersen et al. (2019).

Related literature: Our paper contributes to several streams of the literature. First, multiple studies have asked how to set ask prices optimally. It is likely that sellers begin by contemplating their reservation price, but their ask price does not need to be identical to it (Horowitz, 1992; Taylor, 1999). Ask prices may be linked to demand uncertainty (Herrin et al., 2004; Knight, 2002), the strength of the market (Haurin et al., 2013), seller motivation (Glower et al., 1998, left-digit biases (Repetto and Solis, 2020), and may serve a role in directing search (Han and Strange, 2015). Guren (2018) demonstrates that setting an ask price above the average-priced unit reduces the probability of a sale, while setting the ask price below the average-priced unit only marginally increases the probability of a sale. Similarly, in a study of Danish data, Andersen et al. (2019) find that an ask price that is set lower than what is implied by a hedonic model reduces the spread between the sell price and the price implied by the hedonic model, without a corresponding decline in TOM. For ask prices that are set higher than the hedonic estimate, they find that the sales premium increases, but at the cost of a lower 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 reduce the ask price in order 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 they may be too trusting of their realtor. This is understandable, given how infrequently people sell units, and their lack of experience with this process.

Another stream follows 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. The impact of nominal prices 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. This, 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 may generate more bids and a higher sell price. Einav et al. (2015) find mixed evidence for this using eBay data. In the housing market, Han and Strange (2016) and Repetto and Solis (2020) 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 a larger number of bids. However, our results contain an additional, opposing effect; namely the anchoring effect. The general net result of the two opposing effects is that a strategic mark-down implies a lower sell price.

It has been found that round-number ask prices in eBay auctions signal weak bargaining power, resulting in lower sell prices (Backus et al., 2019). Similarly, Beracha and Seiler (2014) find that the most effective pricing strategy for a seller in the housing market is to employ an ask price that is just below a round number. This is supported by Repetto and Solis (2020), and we replicate this particular mark-down strategy and find similar results. Our paper, however, studies the effects of a more general strategy of setting the ask price lower than an ex ante estimate of the market value regardless of the position on the monetary spectrum of the value of the unit.

Rutherford et al. (2005) find that units that are owned and sold by a real estate agent sell at a premium. Similar findings have been made in Levitt and Syverson (2008). Agarwal et al. (2019) show that, when they buy for themselves, realtors are able to purchase at a lower price. Barwick et al. (2017) find that lower commissions result in lower sale rates and slower sales. We contribute to the literature on agency, since misaligned incentives between a principal (seller) 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 does not benefit the seller, less skilled realtors appear to display behavior that is consistent with a model in which they rationally advise sellers to mark down the ask price in order to expand their customer base and increase their future profits.

The paper is structured as follows. In the next section, we describe the institutional setting of the Norwegian housing market and outline a skeleton model of the general 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 and the exogeneity of the appraisal value. The findings regarding the effects of strategic mark-downs on auction dynamics and outcomes are presented in Section 5. That section also discusses how we deal with unobserved heterogeneity and potential compositional and survivorship biases. In Section 6, we present a motivating model for realtors' incentives when they offer advice on ask prices. In the same section, we show that there are differences in realtors' propensity to use a strategic mark-down, and that the effect of this strategy on future profits differs among types of realtors. Alternative explanations of mark-down strategies, as well as sensitivity and robustness checks, are discussed in Section 7. The final section concludes the paper.

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 several other countries, the buyer does not hire a separate realtor. Norwegian law imposes a responsibility on the realtor to protect the interests of both the seller and the buyer, and he is obliged to advise both the seller and the buyer on issues that may impact the selling process.

There is legislation that regulates who can work as a realtor and use the title of estate agent. In particular, the mediation of housing sales requires that the realtor company holds a permit from the Financial Supervisory Authority of Norway. In certain cases, a sale can also be handled by lawyers, but it is customary for sellers to hire a realtor. Becoming a realtor requires a license, which is obtained after having completed a 3-year bachelor's degree. In addition to the license, two years of practical experience is required before a realtor may assume general responsibility for brokering a housing sale. A realtor's remuneration typically includes a variable fee, which is proportional to the sell price, and it is approximately 1.5 percent.

Appraisers

Until 2016, a person who planned to sell a property typically obtained an appraisal report that included an appraisal value. After a change in 2016, the reporting was redirected to focus attention on technical aspects while the value assessment was left to realtors.[2] Thus, after 2016 we do not have appraisal values.

The practice was that an appraiser would inspect the unit prior to its listing and write a technical report about the general condition of the unit. The report would include a description of the material standard of the unit, its technical condition, and other information. For example, an appraiser would identify the need for drainage, water pressure checks, and potential damp problems.[3] When a unit was listed for sale, the appraisal value and the technical report were known to prospective buyers.[4] In contrast to the situation in other countries, the appraisal value has no bearing on the mortgage amount a prospective buyer is granted and it is therefore not binding for home buyers who finance their property purchase through a bank. In Norway, the market value used by the bank when calculating LTV ratios is simply the purchase price, i.e. the accepted bid, even if that price exceeds the appraised value. The appraisal value therefore functions as an objective, third-party assessment of the market value of the home, but has no further uses.

The realtor's self-marketing tools

Realtors choose their marketing strategy knowing that they need to show evidence of proficiency based on historical records. The sell-ask spread and the sell-appraisal spread are candidate performance measures. The realtors know they are capable of affecting the sell-ask spread by affecting both the sell price and the ask price, but that they can only affect the sell-appraisal spread through the sell price. This simple observation may help explain why it has become custom that realtors use the sell-ask spread in their marketing. Since the sell-appraisal spread involves comparing the outcome with an exogenous variable, the appraisal value, it is a measure over which realtors have less control. They are not obliged to collect and publish evidence on this measure, nor are they incentivized to do so. Even if a

[2] 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 though there are courses that offer appraiser training. A typical background for an appraiser is engineering, and some appraisers thus use the designation 'appraisal engineer'.

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

[4] Appraisers are still typically hired to write a report, but the realtor is responsible for estimating the market value of a unit.

given unit's appraisal value is announced at the time when the online advertisement is posted, it is not a trivial task for a prospective client to obtain a given realtor's historical record of sell-appraisal spreads, because it involves obtaining information from multiple prior transactions. For prospective clients, obtaining this record would involve scraping information from the Internet using code that searches for the realtor's name and the appraisal value for each unit the realtor has been involved with. In all likelihood, no prospective client does this. Instead, prospective clients make use of what is available to them.

This implies that a realtor has control over which performance measure is seen by the prospective client and a game between realtors emerges. A realtor who wants to emphasize his history of sell-ask spreads can do so knowing that the competing measure, the sell-appraisal spread, is hard for a client to obtain. Moreover, a realtor also knows that other realtors know that even if the sell-appraisal spread may be more accurate, they may still prefer to use the sell-ask spread if most other realtors use it. Since the sell-ask spread tends to be larger than the sell-appraisal spread, a Nash equilibrium might emerge in which it is not in any given realtor's self-interest to use the sell-appraisal spread as a marketing tool, especially since it is very costly for high performing realtors to construct measures over their competition.

We, the econometricians, however, can use the sell-appraisal spread as a performance measure, even if it is not easily available to the sellers.

The selling process

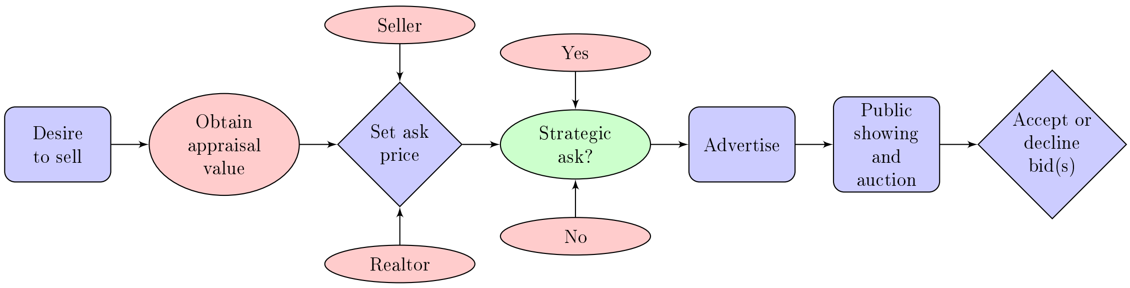
We summarize the selling process in Norway in Figure 1. Having obtained an estimate of the market value, the seller makes a decision on the ask price in consultation with the realtor.

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 as a reflection or guide to the reservation price of the seller at the time the unit is *listed* for sale, but not necessarily at the time the auction begins, since expectations may change over time.

The legislation that governs real estate transactions reflects 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, preventing unfair marketing. The legislation is thus a compromise that maintains the basic contractual principle that a seller may decline any bid, while it also protects the buyer, by stating that the authorities monitor realtors who are associated with multiple sales in which bids above the ask price are declined.

A seller thus is not obliged to accept a bid at, or even above, the ask price. For instance, the seller may update his beliefs about the market value of the unit conditional on number of viewers at the open house, or general market developments, which will lead him to reject offers at or above the initial ask price. The seller may even justify turning down a bid due to a sudden change of heart. 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 certain constraints, in that he does not want to be associated with unlawful ask prices. The realtor is aware that his record must not show a systematic and 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 implication for the seller is that the law does not seriously limit the realistic range from which he can choose an ask price. The legislation consequently incentivizes the realtor to avoid being associated with unlawful ask prices.

Figure 1: The selling process



Notes: The figure illustrates a typical process and is not meant to be exhaustive. Most importantly, we have not attempted to capture the sequencing decision a moving household must make; i.e. the decision whether to buy or sell first. Buying first implies owning two units during the transition process. Selling first implies not owning any units during the transition process. Even though most households generally 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 will circumvent the realtor and contact the seller directly and make a direct bid. Certain nuances are not illustrated in the figure, for example the option to hold several open houses, the decision as to whether both the realtor and seller should be present at the open house, and the dynamic of the auction itself (including bids, expiration bids, and counteroffers from the seller).

Having decided on the ask price, the seller lists the unit for sale, typically using the nationwide online service Finn.no, and national and local newspapers. Most units are listed on Fridays.[5] The advertisement states the date of the unit's open house. In the capital city of Oslo, this typically happens at the weekend, 7 or 8 days after the advertisement was published. The auction begins on the first workday after the last open house, but it is possible and legal to make a bid directly to the seller prior to the open house. Since most units are listed for sale on

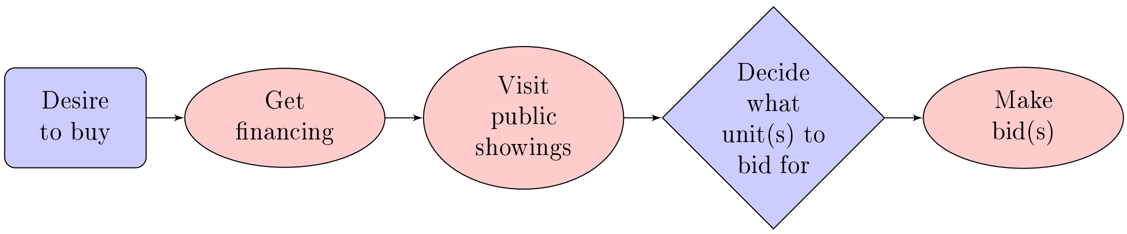
[5]See Figure B.1 in Appendix B.

Fridays, there is fierce competition among sellers to attract people to their open house. Sellers may therefore use a strategic mark-down in order to achieve this goal.

The buying process

We summarize the buying process in Figure 2. A buyer first consults his bank to obtain proof of financing. The buyer documents his and his household's income, debts and assets, and his civil status. The bank assesses the financial ability of the applicant.[6] The search process often commences when financing is secured, but there are also moving owner-occupiers who monitor the market, including visiting open houses, alongside obtaining financing. Proof of financing is not contingent on any particular unit – it reflects the maximum bid a buyer may place in any auction of any unit. In particular, the proof of financing is not dependent upon the appraisal value of a unit, but on the financial situation of the buyer. The calculation of the LTV-ratio is 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 to be exhaustive. The figure does not capture the buy-first or sell-first sequencing decision made by a household. It also does not offer any details on how financing is obtained – by contacting several banks. Nor does it provide details on the multifaceted search-and-match process of how to decide which open houses to visit on the basis of advertisements studied. We do not look at bidding strategies.

Proof of financing is typically valid for three months. During this period, the buyer visits units of interest within his budget. Having found a unit of interest, the buyer places his bid. Since all bids are legally binding, most buyers only bid in one auction at the time.[7]

[6] Regulation of mortgage loans was tightened in 2017. The legislation stipulates a loan-to-value (LTV) ratio of 85 percent and a maximum (total) debt-to-income ratio of 5. Banks must also comply with additional macroprudential requirements.

[7] It is legal, and not uncommon, to place conditions on bids. The conditions usually involve an expiration time, e.g. 30 minutes or noon the next day, but conditions may also include obtaining a statement about access to financing.

The auction

The sale of a unit takes place through an ascending-bid auction. Bids are placed by telephone, telefax, or electronically, using digital platforms, and the realtor informs the active and inactive participants of developments in the auction. All bids are legally binding, as is acceptance of a bid. When a bidder makes his first bid, he typically submits proof of financing, although this practice is cloaked in some technicalities since the buyer does not want to inform the realtor of his borrowing limit. The seller may decline all bids. When the auction is completed, each participant in the auction may view the bidding log, which provides an overview of all of the bids that were placed during the auction. Short expiration times are common, and 52 percent of bids are placed with an expiration time of less than 1 hour. In auctions with more than one bidder, 53 percent of bids are rivalled within 15 minutes. The full distribution of expiration times (in minutes) and the time before a new bid is placed (in minutes) is shown in Figure B.2 and Figure B.3 in Appendix B.

2.2 A skeleton model for a strategic mark-down

There is a growing body of 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 skeleton model has been constructed to shed light on two opposing effects generated by the ask price in a search environment. Our model is meant as a guide to our thinking and as a way to label our analytical tools, not as a fully specified model of all aspects of pricing strategies.

Consider a housing market with N_B buyers and N_S sellers. Units are differentiated both vertically and horizontally.[8] For a given unit h, a buyer b has a latent match quality, $M_{h,b}$ between his preferences, F_b, the vertically-differentiated attributes of the unit, AT_h, and the horizontally-differentiated qualities of the unit, Q_h, meaning that $M_{h,b} = m_h(F_b, AT_h, Q_h)$. The matching function m_h is continuous and differentiable. Thus, for each unit indexed $h = 1, ..., N_S$, there is 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 unit h and buyers $b = 1, ..., N_B$. Buyer b can estimate this latent match

[8] We define vertical differentiation as differentiation in which there is an observable attribute whose ranking is universally accepted. For example, assuming non-satiation, larger is preferable to smaller. We take horizontal differentiation to mean differentiation in which there is no quality whose ranking is universally accepted. This is then a matter of individual taste, and there is no agreement on what is preferable.

quality when he sees an advertisement containing information about vertically-differentiated attributes, AT_h, and a 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 unit h is denoted $\tilde{M}_{h,b}(AT_h, Q_h)$.

Buyer b searches all N_S units on the online advertising platform, but cannot visit the open house for all N_S. He makes a decision to visit the open house for the k units with the highest estimated latent match quality, in combination with his financial constraints. A buyer only visits a unit h if his estimated match quality, based on attributes AT_h, combined with his financial position, justifies it. In order to formalize the process of deciding to visit an open house, 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 function that ranks the visit worthiness of different units. This ranking function g is used as follows. Let A_h be the ask price of unit h and $D_{h,b} = 1$ if buyer b decides that unit h is within the group of these k units and visits the open house of unit h. It is 0 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 is 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 1s is capped at the upper limit k, i.e. $\sum_{i=1}^{N_S} D_{h,b} \leq k$. The buyer visits the k units which score highest on the ranking function $g(\tilde{M}_{b,h}, I_b)$, in which both the estimated match utility and financial position are taken into account.

All buyers make a decision as to whether or not to visit the open house for unit h and we let V be a latent 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 impacts 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 unit h, V_h, and impacts further search and matching, but the seller of unit h does not know the shape of this latent function ex ante. In order to understand the relationship $V_h(A_h)$, the seller of unit h consults his realtor. The number of visitors becomes observable to all participants ex post.

The latent match quality $M_{h,b} = m_h(F_b, AT_h, Q_h)$ between unit h and buyer b is revealed upon inspection of all horizontally-differentiated qualities, Q_h. Buyer b uses the match quality revealed to form his private value of unit 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 open house for unit 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 (WTP) for unit h. The WTP for unit h, $WTP_{b,h}$ for buyer b, is the result of a utility optimization program over the utility extracted from the service stream from unit h and other goods, with the budgetary constraints 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 the ask price, and have dropped the financial constraint in order to ease notation. In buyer b's WTP for unit h, the ask price is entered twice; directly in his estimate of the common value and indirectly through the counting function of number of visitors to the open house. In order to highlight this feature, and with the shortest notation possible:

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

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

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

The total derivative of the WTP 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 WTP. 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 unit.

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, $\frac{\partial V}{\partial A}$, is negative, however, since a higher ask price increases the threshold, $\phi(A)$, in the decision to visit the open house, and so fewer prospective bidders do so.

The first term is the *anchoring effect* and the second term is the *herding effect*. Their relative importance will determine the effect of a change in the ask price on the resulting change in the WTP.[9]

[9] In order to shed light on the relevance of these mechanisms, we explore how the sell-appraisal

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, which is part of the largest Norwegian bank, DNB. The data cover the period 2007–2015, and include information on every bid placed in every auction arranged by DNB Eiendom during this period that resulted in a sale. We have information on each bid, including the unique bidder ID, the time when the bid was placed (to the minute), and the expiration of the bid (to the minute). The data set also contains information on the ask price, the appraisal value, and attributes of the unit. Housing cooperatives (co-ops) typically take on debt in order to renovate the exterior of buildings, remodel kitchens and bathrooms in the different apartment units in the co-op.[10] This debt is called the "common debt", and each member of the co-op 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 133,881 auctions. We remove sales of units with an unknown address and all units transacted over 3 times.[11] We have removed units for which there is no information on the sell price or the ask price. Finally, we have trimmed the data set on the 1^{st} and 99^{th} percentiles of the sell price, ask price, appraisal value, and size.[12] This leaves us with 120,383 auctions, which in turn involve 756,944 bids.

Appraisal values are not reported in all cases,[13] and we are left with 75,908 auctions,[14] which involve 515,053 bids.

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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. The results are summarized in Table B.1 in Appendix B. More bidders increase the sell price relative to the appraisal value. If the ask price impacts the number of bidders, this will thus contribute to a higher sell price. On the other hand, if bidders anchor their WTP at a lower nominal level, this will translate into a lower sell price. In other words, there are two opposing effects.

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

[11] Very few units have been transacted over three times using DNB Eiendom as the real estate agency. Sixty-seven units are reported to have been transacted four times and 28 have been sold five times. One unit is reported to have been sold 13 times.

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

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

[14] We use the term 'auction' here even though the term 'transaction' would be more apt for

We extract information on each auction, including the TOM, 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 into two groups: sales with an ask price below the appraisal value (strategic mark-down) and sales with an ask price that is greater than or equal to the appraisal value.

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 for the period 2007–2015. We distinguish between units with an ask price that is lower than the appraisal value (strategic mark-down) and units with an ask price that is 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 for the period 2007–2015, which was $USD/NOK = 0.1639$.

About half of the transactions have an ask price below the appraisal value. On average, an auction has about two bidders. This is true of 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.

sales processes in which the TOM, and the resulting sales process entails a one-on-one negotiation between the seller and one single bidder.

However, for units with a strategic mark-down, the distance between the opening bid and the appraisal value is greater, 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 result 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 units. Use of strategic mark-downs is observed more frequently in Oslo. In order to explore the sensitivity of our results to the heterogeneity in type and geography, we perform robustness tests by segmenting data by type (detached units and apartments), size (small and large), and price. In addition, we test the robustness of our results to estimation on a non-Oslo segment.

3.2 Realtor data

The data from DNB Eiendom contain a unique realtor identification variable for the realtor who handles 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 that involve units with strategic mark-downs, and how this affects their future sales, we have constructed a separate realtor data set. We summarize some key variables from this data set in Table 2. It is evident that there are great variations in both the number of sales per year and realtors' annual revenue.

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 realtor-level data for the period 2007–2015. The table shows the mean and median of certain 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 have been kept

3.3 Survey data

In order 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 DNB. This survey on the housing market was conducted by DNB in collaboration with Ipsos. It is an on-going project and has been conducted every quarter since 2013. Our questions were included in the 2018Q2 survey. In addition to demographics (gender, age, income, city, education, marital status), people were asked about the housing market, such as the likelihood that they will move, expectations regarding house prices, etc. Two questions in the original survey were particularly relevant to our purpose; namely people's expectations regarding purchase prices, compared with the ask price, and people's perception of the realtor in relation to the sell price. The questions we added were directly related to the role of the ask price itself, and whether people believe that it affects the auction dynamics. While we will refer to the survey results throughout the paper, the detailed results are reported in Appendix A.

4 Empirical approach

4.1 Empirical specification

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

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

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

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

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, $Appraisal_{h,t}$, 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 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 the expected sell price

We use the appraisal value as a benchmark in order to measure the market value of a unit. In this subsection, we will explain why we choose the appraisal value as a gauge of the market price.

Sell-appraisal distribution

The sell-appraisal spread is relatively symmetrically distributed around 0, with a large mass at 0.[15] 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 0.961, a level of explanatory power that further bolsters this claim.

Realtor's role in affecting the appraisal value

One possible concern is that the appraiser is not impartial when deciding on the appraisal value. A particular concern is that realtors who are more likely to offer a mark-down opt for appraisers who more often tend to set high appraisal values. We have investigated this possibility by estimating a hedonic model for appraisal values, using a large set of hedonic attributes.[16] The R^2 from this regression is 0.826, suggesting that a substantial fraction of the variation in appraisal values can be explained by observable attributes of the unit. We then constructed the percentage deviation between the appraisal value and the predicted value. When we regress this variable on realtor fixed effects, to explore how much of the residual variation in appraisal values is related to realtor-specific characteristics, we achieve an R^2 of only 0.006, and only 77 of the realtor-dummies (11.6%) are statistically significant at the 5% level. Pursuing a similar approach for the sell price, the R^2 from regressing the percentage difference between the sell price and the predicted sell price on realtor fixed effects is 0.290, and 495 dummies (74%) are statistically significant at the 5% level. Thus, while realtors seem to have an important role

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

[16] More specifically, the appraisal value is explained by log of size and the square of log size, allowing for different slope coefficients in Oslo and for apartments. The other variables included are year-by-month fixed effects, zip-code fixed effects, dummies for construction periods and lot size above 1,000 sqm, dummies for owner type, and dummies for house type.

in affecting the sell price, there is little evidence that realtors significantly impact the appraisal value.

The ask price and appraisal value distributions

Repetto and Solis (2020) have shown that a left-digit bias, in which humans overweigh the left digit in a number so that 3.99 is perceived as disproportionately lower than 4.00, is present in the Swedish housing market. They further show that a strategy of setting the ask price just below round millions is associated with preferable outcomes for sellers to a strategy of setting it just above.

They find substantially increased sell prices when sellers exploit the left-digit bias, and this finding is a striking example within the subset of mark-down strategies. Their study and the patterns they uncover demonstrate that pricing strategies can work. While they concentrate their focus on one specific strategy, the left-digit mark-down strategy, our aim is to study mark-down strategies in general.

Nevertheless, we do investigate whether a left-digit bias is present in Norway. To that end, we slice all millions of ask prices into 10 equally sized intervals, in order to study the within-million distribution (see Figure B.5a in Appendix B). The first bin covers ask prices within the first nominal NOK 100,000 measured from a million, such as NOK 1,010,000, NOK 2,000,000, NOK 3,050,000, NOK 4,025,000, NOK 5,099,000, etc. The final bin covers ask prices such as NOK 1,990,000, NOK 2,900,000, NOK 3,950,000, NOK 4,925,000, NOK 5,999,000, etc. We find that there is indeed bunching just below the million (the final bin) in ask prices, which indicates that a left-digit bias is also present in the Norwegian housing market. We investigate this specific pricing-strategy in more detail later. At this point, let us address the concern that realtors can nudge appraisers to set appraisal values in intervals that serve as an invitation for a left-digit bias in the ask price. We inspect a similar distribution of appraisal values (see Figure B.5b). The distribution of appraisal values is approximately uniform, and does not exhibit the discontinuities as does the ask price distribution, consistent with the proposition that appraisal values reflect the market value of the unit.

Price growth and low ask

Since the appraisal value is set before the unit is listed for sale, one potential concern is that very few units would be observed as having strategic mark-downs when house prices are rising, simply because the ask price is set after the appraisal value and thus is higher. If house prices rise substantially during the period between the date of the appraisal value and the date of the ask price, it would 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 to lie below the appraisal value, not because of a decision the seller deliberately makes, but because of developments in the market. 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 be somewhat pro-cyclical, unlike the concern raised above.[17]

5 Empirical results

5.1 Baseline results

Table 3 shows our baseline results without unit fixed effects.[18] 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 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 spread between the opening bid and the appraisal value is affected by using a strategic mark-down. The coefficient estimate is -0.957. The interpretation is that a 1 percentage point larger strategic mark-down is associated with a 0.96 percentage point reduction of the opening bid-appraisal spread.[19]

The coefficient estimate of the sell-appraisal spread is -0.768 and the estimate is statistically significant. The coefficient estimate of the sell-ask spread is 0.080, nonetheless, and is statistically significant. If this estimated coefficient had been 0, a reduction in the ask price would not have been associated with a change in the sell-ask spread.

In specifications (II), (III), (IV), and (V), we sequentially add controls for zip code FE (II), attributes of the unit (III)[20], realtor fixed effects (IV), and realtor-office fixed effects (V). The results are robust along the specifications.

[17]See Figure B.6 in 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).

[18]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.

[19]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. In order to ease reading, we use the term “percentage point” to refer to a fractional change of 0.01.

[20]We add the following attributes: the logarithm of the size, the square of the logarithm of the size, unit type, and a lot size dummy if the lot is larger than 1,000 square meters, construction period dummies, and dummies controlling for type of ownership.

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): + Realtor FE	0.002	-0.959***	-0.761***	0.081***
	(0.002)	(0.008)	(0.008)	(0.008)
No. obs.	39,661	39,626	39,661	39,661
Adj. R^2	0.133	0.355	0.347	0.215
(V): + Realtor Office 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 an increase in 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, and gradually add controls for year-by-month fixed effects in (I), zip code fixed effects in (II), hedonic attributes (the logarithm of the size, the square of the logarithm of the size, unit type, and a lot size dummy if the lot is larger than 1,000 square meters, construction period dummies, and dummies controlling for type of ownership) in (III), realtor fixed effects in (IV), and realtor office fixed effects in (V). 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.

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. Our data contain 2,679 units that have been sold at least twice. Table 4 tabulates results based on estimating the (6) for different outcome variables.

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 when the strategic mark-down is increased (lowering the ask price relative to the appraisal value). The sample covers the period 2007–2015. We only consider 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, 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.

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. A positive sign thus 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 the impact of a strategic mark-down on the opening bid-appraisal spread. The coefficient estimate is -0.958. The interpretation is that a 1 percentage point greater 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 1 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 is statistically significant. If this estimated coefficient had been 0, an increase in the mark-down, i.e. a reduction in 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 0, an increase in the strategic mark-down is clearly associated with an increase in the sell-ask spread. We will argue below that this is a useful result, because it is consistent with the hypothesis that manipulating the ask price has a positive impact on the sell-ask spread. We also argue that this is used by realtors as a gauge of performance when they recruit new clients.

The overall impression of these regressions is that we find statistically significant estimated coefficients with a high explanatory power. For the sell-appraisal spread regression, the adjusted R^2 is 0.75, which is considerable, when one considers that the variation in the appraisal value explains much of the variation in the sell price, so the sell-appraisal spread is a residual.

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 greater strategic mark-down is associated with a lower sell price as measured against a neutral yardstick; i.e. a lower sell-appraisal spread.

Time-varying unit characteristics:

Other forms of unobserved unit heterogeneity may 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 spread 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 may make mistakes, some appraisal values may be set too 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 in the event of negative qualities that are not observed by the appraiser, but are known to the seller and the realtor. One example is 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 setup. Instead, this unobserved heterogeneity is time varying. In order to investigate the possible need for renovation, we have acquired a transaction data set for units that have been renovated, and for which we know the year of renovation.[21] In order to explore whether there is a difference in renovation frequency between the group of units with a strategic mark-down and the group of units with an ask price that is greater than, or equal to, the appraisal value, we look at changes in renovation frequencies in the years preceding and following the sales year.

The results are summarized in Table 5. It is clear from the table that there are no significant differences in renovation frequency in the year in which a unit is sold. The same is true for the years preceding a sale and for the years following a sale. The exception is 2 years after sale, in which units with a mark-down have a somewhat smaller chance of being renovated – the opposite of what would be implied by the concern raised above.

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
$\mathbb{1}\,(Mark-down>0)$	-0.003	-0.004	-0.006	-0.007***	-0.001
	(0.005)	(0.005)	(0.006)	(0.002)	(0.001)
Observations	16717	16717	16717	16717	16717

Notes: Data on the year of renovation were obtained from Eiendomsverdi. The table was generated as follows. In our first regression, we defined our dependent variable as unity if the time of renovation was exactly equal to the year of sale, and 0 otherwise. We then regressed this outcome variable on an intercept and a variable that is unity if the sale involved a strategic mark-down, and 0 otherwise. This regression amounts to testing whether units with a strategic mark-down have a higher renovation frequency. We proceeded in 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. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

[21] The data have been provided by the data-analytics firm Eiendomsverdi.

Unobserved seller heterogeneity

It is possible to raise the concern that what we characterize as a strategic choice by a seller is not actually a strategic choice, but rather reflects an inherent trait of the seller, a trait the seller might even be unaware of himself. Assume that there are two kinds of sellers: one is patient and the other one is impatient. It is fathomable, even if not necessarily plausible, that an impatient seller will tend to both use a strategic mark-down and accept a low bid too soon. In this event, the impatient seller is involved in a sale with a strategic mark-down and that is characterized by a lower sell price, compared to the appraisal value, more often than the patient seller. This unobserved seller heterogeneity would bias our results towards magnifying the negative effect of a strategic mark-down on the sell price.

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

Second, it is reasonable to believe that impatience affects the TOM in that impatience leads to a lower TOM among units with strategic mark-downs. The TOM is generally short in Norway, and 90 percent of the units in our sample were sold within 100 days. This suggests that the incentive to sell quickly may be less relevant in the Norwegian housing market than in many other countries.[22] However, we explore how a strategic mark-down affects the probability of a quick sale and find no association between the use of a strategic mark-down and the probability of a quick sale. A strategic mark-down could also be a 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.[23]

[22] We have also looked at the association between time-on-market and the ask price, using different sets of control variables. Results are summarized in Table B.2. in Appendix B. It is evident that the link between the ask price and TOM is weaker in Norway than what is found in other countries – especially when including a rich set of controls.

[23] In order to explore this possibility, we identify units that have sold quickly and slowly, compared with other units in the same municipality and in the same quarter. A quick sale is defined in two ways: units that sell more quickly 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

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	0.052*	-0.948***	-0.970***	0.063
	(0.028)	(0.122)	(0.130)	(0.133)
No. obs.	5,582	5,572	5,582	5,582
Adj. R^2	-1.578	-0.496	-0.555	-1.516
Controls:				
Common debt	✓	✓	✓	✓
Appraisal	✓	✓	✓	✓
Realtor FE	✓	✓	✓	✓
Realtor office FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
First stage results:				
	Parsimonious	Fully specified		
Frac. mark-down in zip-code	5.405***	4.217***		
	(0.418)	(0.450)		
Adj. R^2	0.028	0.752		

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 fraction of units listed with a mark-down within the same zip-code and quarter as an instrument. The sample covers the period 2007–2015. We only consider units that have been sold at least twice, in order to control for unit fixed effects. We also control for common debt, appraisal value, realtor fixed effects, realtor office fixed effects, and year-by-month fixed effects. The lower section of the table shows the first-stage results. The term "Parsimonious" refers to a regression in which the strategic mark-down is only regressed onto the instrument, while 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.

We have also explored how the likelihood of expiration bids is affected by a strategic mark-down. We have therefore identified auctions in which at least 1 bid has expired before the unit was sold. In these auctions, the seller has decided to

the probability of a slow sale and the use of a strategic mark-down. Slow sales are defined as units with a TOM greater than the 75^{th} and the 90^{th} percentile of the TOM distribution in the same municipality and quarter. For both slow and quick sales, we follow units that are sold at least twice in order to control for unit fixed effects and estimate a set of logit models. The results are summarized in Table B.3 in Appendix B.

decline at least one bid, at 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 a expiration bid and a strategic mark-down.[24]

Finally, we have employed an instrumental variable approach in order to control for latent seller types. Our instrument is the fraction of units within the same zip-code and sales quarter that are listed with a mark-down.[25] This instrument is inspired by Guren (2018), who studies strategic complementarity in ask prices, i.e. that optimal ask prices are increasing in the mean ask price across other comparable units. Our exclusion restriction rests on the assumption that there is no geographical clustering of a seller type that both uses mark-down strategies and is impatient. Instead, we assume that the propensity to use a mark-down strategy is orthogonal to type, but associated with the frequency and magnitude with which other sellers use mark-down strategies.[26]

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

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

The summary statistics in Table 1 show that units listed with a strategic mark-down tend to be smaller and have a higher appraisal value. Apartments are represented more often among the sample of units with a strategic mark-down. Low ask price units are sold more frequently in Oslo. We have also seen that there is an increased, although minor, probability of slow sales for units listed with a strategic mark-down.

There are also several differences between the selling process for co-ops and owner-occupied units. Most importantly, co-ops allow their members to enter into the bidding process and buy the unit at the same price as the highest bid after a given deadline. The highest bidder will not be able to bid again, but will lose the auction. Thus, in bidding for a unit in a co-op, a bidder not only competes with other bidders, but also with co-op members with the option to match the bid and

[24] The results are summarized in Table B.4 in Appendix B.

[25] We have also looked at the median mark-up among units sold within the same zip-code and quarter as an alternative instrument. Results are robust to this alternative instrument.

[26] In order to partially investigate the orthogonality condition, we regress the residuals from the baseline regressions (as reported in Table 3) on the proposed instrument. The results are tabulated in Table B.5 in Appendix B. There is no association between the residuals from the baseline regressions and the suggested instrument.

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 the impact on different auction outcomes by increasing the strategic mark-down (lowering the ask relative to the appraisal value) for different subsamples. The subsamples cover the period 2007–2015. We only consider units that have been 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.

acquire the unit. In order to prevent that, the bid must be 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 with an appraisal value that is below the median in their municipality versus units that are priced above the median. We perform a similar robustness test based on size segmentation and TOM segmentation.[27] Furthermore, we redo all of 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 the detailed results are reported in Table 7.

Survivorship bias

It is fathomable that a strategic mark-down implies a higher probability of sale. In order to examine the possibility of a survivorship bias, we extract information on all units that were registered for sale in Norway for the six-year period 2010-2015 from the firm Eiendomsverdi. The data contain all units that were put up for sale on the online platform Finn.no and the data set contains 288,834 observations. The data are partitioned into four segments: units with a negative mark-down, i.e. a mark-up; units with a small, positive mark-down (between 0 and 5 percent); units with a large mark-down (larger than 5 percent); and units with a mark-down equal to zero. The latter segment is default.

The segment with negative mark-downs is small and contains 9,696 observations. The segment with small, positive mark-downs is large and contains 106,441 observations. Regressions (1) to (4) are probit models of the probability of a sale after 1 year. Model (4) includes hedonic attributes, year-by-month fixed effects, and county fixed effects.

The estimated coefficient for a negative mark-down (a mark-up) is negative. The implication is that using an ask price that is larger than the appraisal value reduces the probability of a sale within one year. This is similar to the findings in Andersen et al. (2019) for Denmark. The estimated coefficient for a small, positive mark-down is 0.04, but statistically insignificant. The interpretation is that there is a slight tendency of a small mark-down to increase the probability of a sale, but that the effect is so small that it is not statistically significant at the conventional levels, which is consistent with results in Guren (2018) and Andersen et al. (2019). Large, positive mark-downs are associated with decreases in sale probability.

To make interpretations easier, we have computed the estimated probability of a sale for each of the 288,834 units observed, and inspected the distribution within each segment. The 10th percentile of the estimated sale probability within the segment with negative mark-downs (i.e. mark-ups) is 0.968. The 10th percentile of the estimated sale probability in the segment of small, positive mark-downs is 0.995. We see that there is a pattern consistent with the idea that a small mark-down increases the probability of a sale, but that the effect is not large. Moreover, we observe that in Norway, most listed units are actually eventually sold.

[27] Since we are looking at repeat sales, we require that the unit belongs to the same category in all sales.

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

6.1 A model of realtor incentives

In our model, the realtor maximizes profits over two periods: the present and the future. Realtors compete for contracts and sellers screen realtors in order to find the one that is best suited to advise on selling the unit. Realtors have one of two skill types, θ, with either a high performance score (H) or a low performance score (L). The realtor knows his own type, but the seller does not know realtor types. A realtor enters into a second-period contract after the completion of a first-period sale. A given realtor, r, will know that the first-period sell price $P_{1,r}$ and ask price $A_{1,r}$ will impact on the probability of winning a contract in the second period, as 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 measure when screening for a realtor. Realtors report their sell-ask spreads and the seller observes these spreads.

Assume an unobserved density $f(P_h)$ for the sell price of unit h among 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 measure for realtor r. This performance measure would be the spread, $SE_h = \frac{P_{h,1,r}-P_h^\star}{P_h^\star}$, and we denote it as the sell-expected spread for unit h and realtor r. This would be a natural gauge of performance quality if it were observable.[28]

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 because it is custom among realtors to use it as a marketing tool. It affects the probability of winning a second-period contract for unit 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, suppress realtor subscript r and unit subscripts h and j for the sake of simplicity. δ is a discount factor. $R()$ is an unspecified revenue

[28]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, as is discussed above. Both sellers and realtors know that this is not publicly available and sellers and realtors know that others know.

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 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.[29]

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

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

in which we have disregarded 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 findings suggest that the sign of the right-most factor is positive, meaning that the first term is positive.

The second term is the effect on the probability of winning 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

[29] In Norwegian real estate auctions, the commission may consist of a fixed fee component and a fraction of the sell price. The legislation stipulates that the fraction must be constant. Incentives schemes in which the commission is a proportion of the sell-ask spread or a stepwise function of fractions above a pre-specified threshold are no longer allowed.

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. Again, our empirical results suggest that the sign of the right-most factor is positive, meaning that the second term is also positive.

The third term is the effect on the probability of winning 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, meaning that the third term is unambiguously negative. This effect offers an incentive for a realtor to reduce the first-period ask price.

The total effect on profits depends on the relative magnitudes of the first two terms versus the last term. Our empirical objective is to estimate the net effect. Since the partial derivatives are functions of the realtor type, we will also explore differences between realtors, after having classified them using our performance measure, the sell-appraisal spread.

6.2 Empirical results on realtor behavior

What characterizes realtors that 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 will 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 the ask price is not fully passed through into a similar reduction in the sell price. This spread serves as a marketing device for realtors when they approach prospective clients and seek to signal skills.

The implication is that realtors not only take into account how the ask price affects the current sell price, but also how it affects their track record in terms of the sell-ask spread. Since survey results (see Figure A.1a in Appendix A), suggest that respondents trust the advice they receive from their realtor when they are making decisions regarding the ask price, this scenario is plausible. Furthermore, as is shown in Figure A.1b, respondents tend to believe that the realtor is instrumental to achieving the sell price.[30]

[30] Our empirical findings are consistent with this belief. In particular, we have constructed the percentage deviation between the sell price and the predicted value from a hedonic model. We regress this percentage deviation on realtor fixed effects, to explore how much of the residual variation in sell prices is related to realtor-specific characteristics. The R^2 is 0.290, and 495

In order 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 randomly partition each realtor's sales into two equally sized sets by splitting sales for each year in two. This leaves us with two sets of observations for each realtor for each year. For each of the sets, we calculate the mean sell-appraisal spread for the realtor. We then compare the mean sell-appraisal spread of each realtor to the distribution of all realtors' mean sell-appraisal spreads in the municipality in which the realtor is active. We rank using quintile groups. If a realtor belongs to the first quintile in both sets, we characterize this realtor as having a "Very low performance score".

If the realtor belongs to the highest quintile in both sets, he is characterized as having a"Very high performance score". This procedure allows us to classify realtors using five categories of realtor type θ. The set of realtor types, Θ consists of these 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 across sets are discarded. In order to explore whether the realtor type has an impact on the likelihood of using a strategic mark-down, we estimate the following logit specification:

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

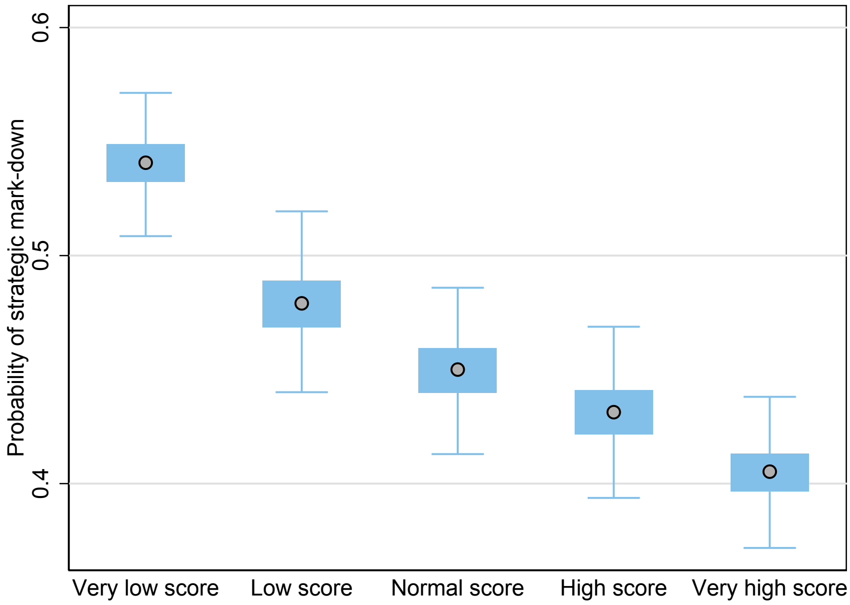
in which $\theta_{h,t,r}$ represents the realtor type θ of realtor r associated with the sale of unit h at time t. The subscript FE is short notation for year-by-month, realtor office, and area fixed effects. γ is a five-by-one vector that contains the five coefficients representing the realtor type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

Since the partitioning into sets is random, we repeat this exercise 1,000 times in order to perform a non-parametric Monte Carlo simulation of the estimation uncertainty. Box plots of the marginal effects of 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. A visual inspection clearly identifies a pattern. Realtors with a very low performance score are more likely to be associated with sales in which a

dummies (74%) are statistically significant at the 5% level.

strategic mark-down has been used. Realtors with a very high performance score are less likely to be associated with sales in which a strategic mark-down is used. In fact, the likelihood of using a strategic mark-down decreases monotonically for realtor performance.

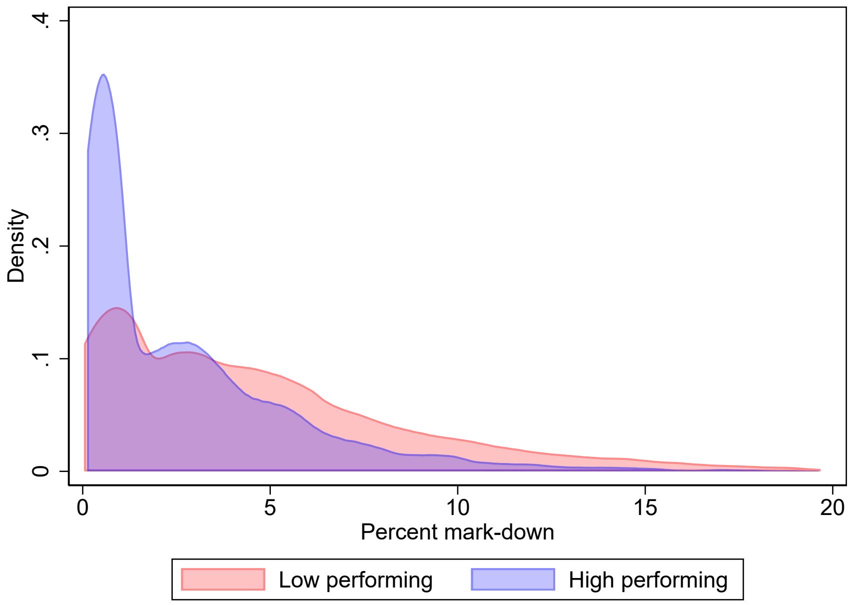
Figure 3: Realtor score on performance and propensity to offer a strategic mark-down. Norway, 2007–2015



Notes: The figure shows box plots of the estimated probability of being involved with sales with a strategic mark-down among different types of realtors. For each realtor and each year, we split the sample in two, randomly. Then samples are collected across years for each realtor. In each part, realtors are ranked by their median sell-appraisal spread. We then categorize realtors based on quintile grouping. If a realtor belongs to the same quintile in both sets, 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 the realtor's quintile category and fixed effect controls for year-month, realtor office, and area. We repeat this exercise 1,000 times in order to calculate bootstrapped confidence intervals.

Although less skilled realtors more often are associated with the use of a strategic mark-down, this strategy is also quite common among high-performance score realtors. To shed more light on the practice, we also examine the size of the mark-down. We employ the same classification approach as above, but use the full sample, and – hence – only one draw. We then compare the distribution of

Figure 4: Realtor skills and size of mark-downs. Norway, 2007–2015



Notes: The figure shows the kernel density of percentage mark-downs for very low performance score realtors (red) and very high performance score realtors (blue). Very low performance score realtors are defined as realtor-year combinations in which the mean mark-down of the realtor belongs to the lowest quintile of all realtors' mean sell-appraisal distribution in the municipality in which the agent is active. Likewise, very high performance score realtors are defined as realtor-year combinations in which the mean mark-down of the realtor belongs to the highest quintile of all realtors' mean sell-appraisal distribution in the municipality in which the agent is active.

percentage mark-downs among the very high performance score realtors (highest quintile) and the very low performance score realtors (lowest quintile). The mark-down distributions for the two types are shown in Figure 4. The pattern is that mark-downs among high performing realtors tend to be smaller than mark-downs among low performing realtors.

Do realtors benefit from advising the use of strategic mark-downs?

Our simple motivating model for realtor incentives in advising sellers on how to set the ask price suggests that there may be differences among realtor skill types as to whether the advice to pursue a low ask price is a profit-maximizing strategy. Essentially, the realtor can advise the seller to either use a strategic mark-down or not. In order to explore the hypothesis that realtor advice is related to the realtor skill type, we follow the same procedure as above. We characterize realtors' skill levels each year, to maintain the possibility that a given realtor can change skill type.

We do this by a random partitioning of each realtor's yearly sales in two equally sized sets. Then, we characterize the performance of each realtor in each year. Here, we use two levels of performance quality, and say that a realtor is of the type "High performance score" in a given year if his mean sell-appraisal spread is larger than, or equal to, the median of all realtor's mean sell-appraisal spreads in the municipality in which the realtor is active. Likewise, a realtor is characterized as being "Low performance score" in a given year if his mean sell-appraisal spread is lower than the median of all realtor's mean sell-appraisal spreads in the municipality in which the realtor is active.

We then test whether a change (in the size) of strategic mark-downs 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 as having either a High performance score or Low performance score in year $t-1$, and estimate the following equation for the two skill types:

$$\Delta\text{Revenue}^{\theta}_{r,t} = \alpha^{\theta,m} + \beta^{\theta,m}_{j} + \eta^{\theta,m}_{t} + \zeta^{\theta,m}_{l} + \gamma^{\theta,m}\Delta\text{Strategic mark-down}^{Median}_{r,t-1}$$

in which $\Theta = \{\text{High performance score}, \text{Low performance score}\}$. α is an intercept, β represents realtor office fixed effects, η represents year fixed effects, and ζ are area fixed effects. Index r refers to the realtor, j to the office the realtor works at, t to time, l to municipality, and m indicates that coefficients will vary across random draws. We repeat this procedure 1,000 times in order to perform a non-parametric simulation of the distribution of the estimates.

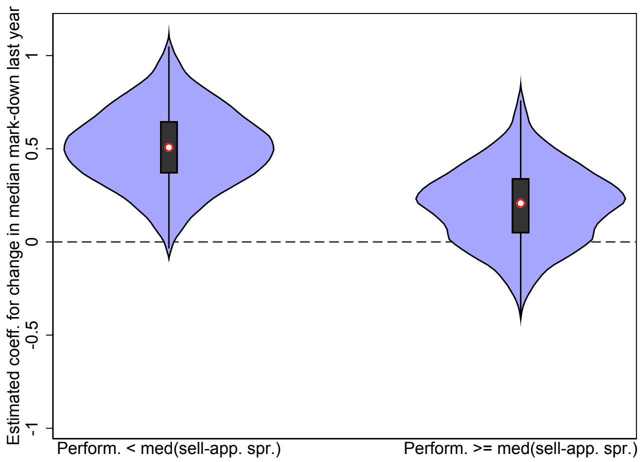
The notation $\Delta\text{Revenue}_t$ refers to the change in revenue from $t-1$ to t and $\Delta\text{Strategic mark-down}_{t-1}$ to the change in (the size of) strategic mark-downs between $t-2$ and $t-1$. The change in the strategic mark-down is measured using median mark-downs for realtors. Our parameters of interest are $\gamma^{\theta,m}$, which measures the effect on revenue change of a mark-down change.

Figure 5 shows violin plots for estimated coefficients for the two groups. The violin plots show the full density based on all 1,000 draws.[31] Our results suggest that a change in (the size of) strategic mark-down from $t-2$ to $t-1$ is associated with positive, but statistically insignificant, effect on the change in future revenue for High performance score realtors (the right-most plot of the distribution of coefficient estimates clearly covers 0). For Low performance score realtors,

[31] The average coefficients and standard deviations based on the 1,000 draws are summarized in Table B.7 in Appendix B.

there is a statistically significant 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 0 at a high level of statistical significance. The mean estimate is also higher for this group. The extent to which changing practices regarding strategic mark-downs have an effect on future revenue differs between the two types of realtors, as measured by the performance measure sell-appraisal spread. The results are consistent with the notion that High performance score realtors focus attention on the sell price in order to increase the sell-ask spread, while Low performance score realtors focus attention on the ask price.

Figure 5: 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 is associated with revenue change (lower panel) for two groups of realtors: those who in year t achieved a mean sell-appraisal spread above, or equal to, the median of all realtor's mean sell-appraisal spreads in the municipality in which the realtor is active, and those who had a mean sell-appraisal spread below the median of all realtor's mean sell-appraisal spreads in the municipality in which the realtor is active. In order to rule out spurious effects, we split realtor-year observations randomly in two, and require that a realtor belongs to the same group in both subsamples in order to be part of the sample. This exercise is repeated 1,000 times, giving us a bootstrap estimate of the distributions.

7 Robustness and sensitivity checks

Base sell probability

Guren (2018) finds a base probability of sale within 13 weeks of 0.48, and that increasing the ask price by 1 percent is associated with a decrease in sale probability of 0.027. Based on this base rate, we note that there are differences in the flow rate in the U.S. and the Norwegian housing markets, since a higher fraction of units are sold within 13 weeks in Norway. For units with appraisal values across all regions and all years, 89.95 percent of units were sold within 13 weeks in our data set. This percentage displays cyclicality, and ranges from 82.69 (2009) to 94.23 (2007). In the more liquid capital city Oslo, the range varies from 88.10 (2009) to 96.76 (2015).[32]

Mark-down propensities across age groups

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 raise 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.7 in Appendix B, we plot the frequency of sales with a strategic mark-down across different age groups based on a data set compiled by the bank-owned analytics firm, Eiendomsverdi. This figure shows that while sellers in the age group 20-30 years tend to use mark-downs at a propensity of 50.82 percent, the propensity falls to 36.63 percent for sellers above 60 years of age. This is consistent with, but not conclusive evidence of, younger sellers being more keen to heed mark-down advice from realtors. It is also consistent with an element of learning among sellers.

Using a hedonic model to measure the market valuation

An alternative approach to using the appraisal value as an estimator of market value is through the estimation a hedonic model, as in Andersen et al. (2019). 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 is closely related to 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

[32] These numbers are not reported in any table, but are computed separately using our data.

considerable, compared to use of the appraisal value, as a physical inspection by an appraiser involves inspection of the variables that are omitted in the hedonic model. However, use of a hedonic model offers two advantages. First, a model contains no risk of a strategic element, while this is a small albeit not ignorable risk with the appraisal value, in that the appraiser's estimate is made on a discretionary basis. Second, the model contains no subjective component or lack of current knowledge of the market, which is fathomable for some appraisers. We summarize results from the hedonic regression model in Table B.8 in Appendix B. The results of our re-estimation of the regressions for auction outcomes on the strategic mark-down when the appraisal value is replaced by the model-predicted price are presented in Table B.9 in Appendix B. The results are robust to this alternative approach.

Robustness to use of full transaction data

Our analysis has used bid logs and auction data from a single company, DNB Eiendom. There may be biases in the type of units and clients served by DNB Eiendom. In order to examine the extent to which this source of data may affect our results, we also acquired transaction data from Eiendomsverdi. Table B.10 in Appendix B summarizes the data in a check for balance. It is evident that the data from DNB Eiendom are comparable to the full transaction data. The main reason we do not use the full transaction data set from Eiendomsverdi as our default is that these transaction data do not contain information on the individual bids in each auction. This lack of auction-specific information precludes investigations into elements of the herding effect (number of bidders), and the anchoring effect (nominal value of the opening bid).

Moreover, the data from Eiendomsverdi do not let us control for realtor or realtor office fixed effects, so we cannot use these data when investigating the impact of realtors on sellers' decisions. However, as a robustness check, we have compared our findings regarding the sell-appraisal spread, the ask-appraisal spread, and the TOM from data from DNB Eiendom to data from Eiendomsverdi. None of our results have been materially affected by the choice of data source, and the detailed results are reported in Table B.11 in Appendix B.

Left-digit bias

There are signs of a left-digit bias, in which sellers set an ask price just below round millions, in the Norwegian housing market (see Figure B.5 in Appendix B). In fact, sellers who receive a round-million appraisal value have a mark-down frequency of 64.2%, whereas sellers who do not receive a round-million appraisal value have a mark-down frequency of 44.3%. We have followed Repetto and Solis (2020) to explore the effect of this particular strategy on sell prices. Their specification takes the following form:

$$log(sell)_i = \beta_j + \gamma \mathbb{1}\left(log(ask)_j \geq c_j\right) + \theta_j \left(log(ask)_i - c_j\right) \mathbb{1}\left(log(ask)_i \geq c_j\right) + \boldsymbol{\delta}'\boldsymbol{X}_i + \epsilon_i$$

in which c_j is the (logarithm of the) relevant round-million threshold for ask_i, β_j are threshold-specific intercepts, and $\boldsymbol{X}_i$ comprise controls. Following Repetto and Solis (2020), we estimate this specification for all ask prices in the interval NOK 100,000 below to NOK 100,000 above the relevant round-million threshold.[33] We estimate one specification without controls and one with controls.[34]

Results are reported in the first two columns of Table B.12 in Appendix B. Similar to Repetto and Solis (2020), we find that there is a reduction in final prices at round-million thresholds, and it seems strategically preferable to set the ask price marginally below the round million than marginally above the round million when faced with a round-million appraisal value.

We take the analysis one step further to bridge it with our approach of using the appraisal value as a yardstick for the market value and also to use appraisal value for possible unobserved heterogeneity. In particular, we substitute the sell price as the dependent variable with the sell-appraisal spread, and re-estimate the two specifications. Results are summarized in the final two columns of Table B.12. It is evident that the positive effect of setting the ask price just below the round million disappears once we consider the sell-appraisal spread. In Table B.13, we report results for a segment consisting of only Oslo. In this case, we do find a positive effect of a left-digit strategy even when the sell-appraisal spread is considered – suggesting that the finding of Repetto and Solis (2020) also have some relevance in Norway – at least in a liquid market like Oslo.

TOM for different realtors

To see whether there are systematic differences between TOM across different realtors, we compare the TOM-distribution of high- and low-performing realtors, using a similar classification as in Section 6.2. Kernel densities for the two groups are shown in Figure B.8, and – if anything – the high-performing realtors have a shorter TOM than low-performing realtors, suggesting that there is no evidence

[33] While Repetto and Solis (2020) constrain their sample to units with a maximum ask price of SEK 5.1 million, we do not impose any constraint on the maximum ask price. That said, our results are similar if we constrain at NOK 5.1 million.

[34] The controls are log of size and the square of log size, allowing for different slope coefficients in Oslo and for apartments. The other controls are dummies for construction periods and lot size above 1,000 sqm, dummies for owner type, and dummies for house type. In addition, we include year-by-month-by-municipality fixed effects, zip-code fixed effects, realtor fixed effects, and realtor-office fixed effects.

that low-performing realtors systematically sell cheaper in order to deliver quicker sales. In Figure B.9, we compare realtors whose median sale is a mark-down to realtors whose median sale is not a mark-down. Again, if anything, TOM is slightly lower among realtors who do not typically offer a mark-down.

Variations over the housing cycle

In order 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 across years for each of the variables are plotted in Figure B.10 in Appendix B. Although the effects on the number of bidders have been estimated less precisely, all of our findings are broadly robust to this exercise.

Non-linearities

There may be differences in the use of a large or small mark-down, i.e. an ask price that is much lower or only marginally lower than the appraisal value. In order to explore this possibility, we partition our data into four mark-down 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. The results are summarized in Figure B.11 in Appendix B. The pattern is intact.

Mark-up versus mark-down

Another non-linearity that could be present is that there is a difference between offering a mark-down and a mark-up. While a mark-up is used only in 3.58% of the transactions, we have re-estimated (6) our regressions by allowing an additional effect of the mark-down variable when it is negative (mark-up). Results are reported together with baseline results in Table B.14. There is some evidence that there may be a stronger effect (in absolute value) of using a mark-up, although the coefficient is only statistically significant at a 10% level. In sum, we find that the effects of mark-down and mark-up strategies on the sell-appraisal spreads are symmetric. However, as shown previously, there is little evidence of a mark-down strategy affecting sale probability or TOM. However, we have found evidence that a mark-up strategy is associated with a higher TOM. This is consistent with the findings in Guren (2018) and Andersen et al. (2019).

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. Which effect is stronger is an empirical question. 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 fewer sellers to use this strategy. Conversely, if the answer is that it increases the sell price, one would expect more sellers to use this strategy. Yet it turns out that about 50 percent of sellers use the strategy while 50 percent of sellers do not. This article first demonstrates that a strategic mark-down reduces the sell price, then attempts to explain why some sellers still use the strategy.

All else being equal, a 1 percent reduction in the ask price tends to be associated with a 0.9 percent reduction in the sell price. The reason for this is that the anchoring effect overwhelms the herding effect. The herding effect exists, as a strategic mark-down is associated with the presence of 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 and future profits. If a realtor advises the use of a strategic mark-down in the current period, and the seller follows this advice, this results in a lower sell price. The lower sell price reduces current profits but increases future profits, as it increases the sell-ask spread. The sell-ask spread is a marketing tool used by realtors to recruit new clients. However, there are two ways of increasing the sell-ask spread: one can increase the sell price or one can reduce the ask price. Lowering the ask price is naturally self-defeating if such a decrease also leads to a similar reduction 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 with a complete pass-through. A reduction in the ask price does indeed increase the sell-ask. This is key to understanding how different realtor types are associated with different practices.

The type of advice provided by a realtor appears to be related to the type of 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 measure, 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 declining link between the frequency of being associated with a strategic mark-down and the performance measure. 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 realtors experience in the next period after they were associated with sales with mark-downs during this period. There is an association between a change in strategic mark-downs in the current period and a change in revenues in the future period for low-performing realtors. There is less evidence of such a link for high performance score realtors. It thus seems that low performance score realtors maximize inter-temporal profits by advising clients to use strategic mark-downs.

One could fathom that even if a strategic mark-down is not associated with an increase in the sell-appraisal spread, it could be associated with a higher sale probability or a lower TOM. We do not find strong evidence to support these propositions. In fact, high performance realtors are associated with lower TOM. When we estimate the probability of fast sales and slow sales, we do not find statistically significant effects of mark-downs on the probability of fast sales. In fact, we do find a slight increase in the probability of a slow sale for units listed with a mark-down. However, a small mark-down is indeed associated with a marginally higher, albeit statistically insignificant, sale probability within one year.

If a strategic mark-down benefits low performance score realtors, but not sellers, one would expect sellers to discover this. However, even though a housing unit is an asset with a considerable value, it is an asset that sellers have little experience in selling, nonetheless. Individuals do not often sell real estate. Using survey responses, we find that sellers tend to listen to and trust realtors. However, we do see a tendency indicating learning among sellers, since older sellers are less likely to offer a mark-down than younger sellers.

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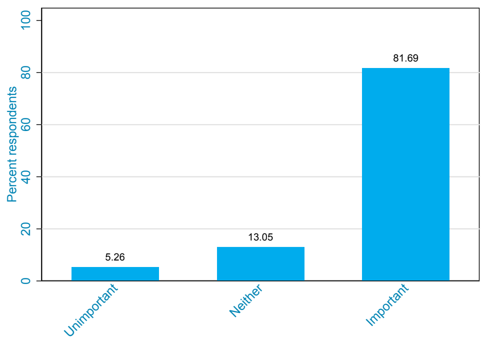
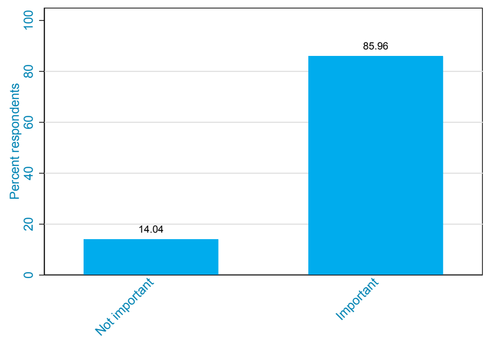
A Survey results

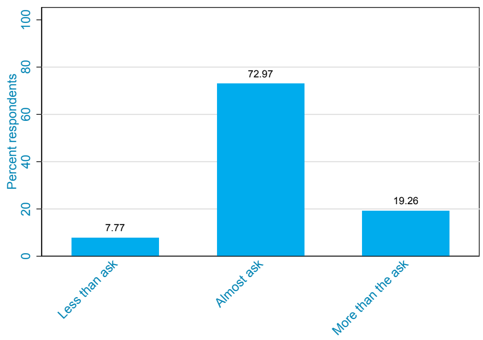
Figure A.1: Survey results, continues on next page



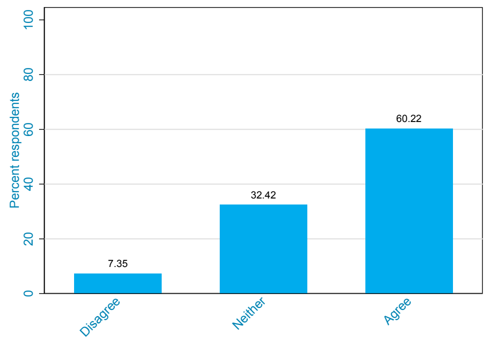
(a) How important is the realtor in deciding the ask price?



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



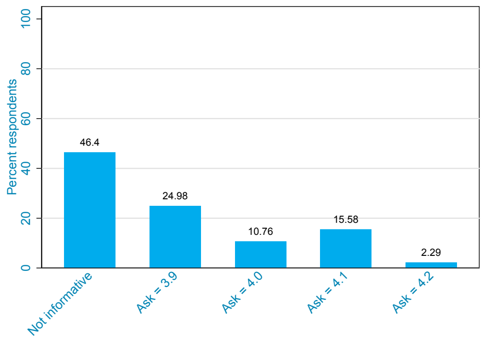
(c) What do you expect regarding the purchase price when you buy?



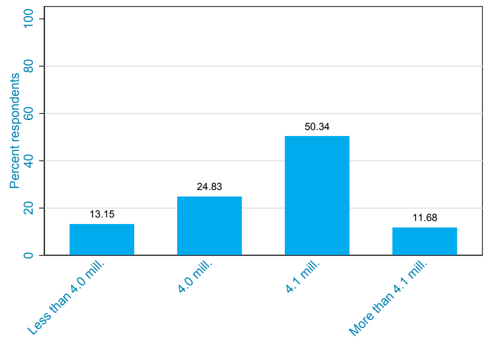
(d) Do you think a lower ask price attracts more bidders?

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?



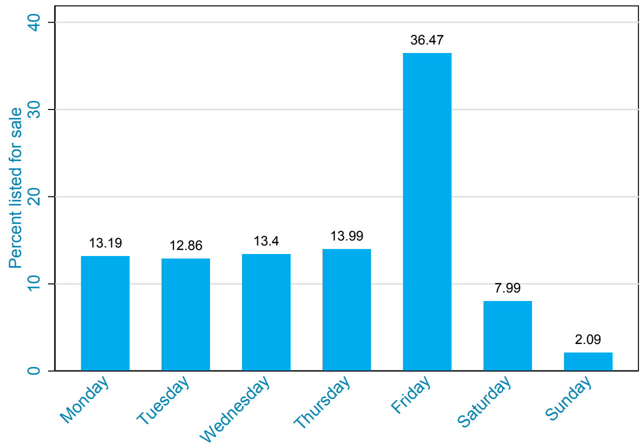
(f) Your house is valued at 4.1 million. What ask price would you set?

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

Day of advertising

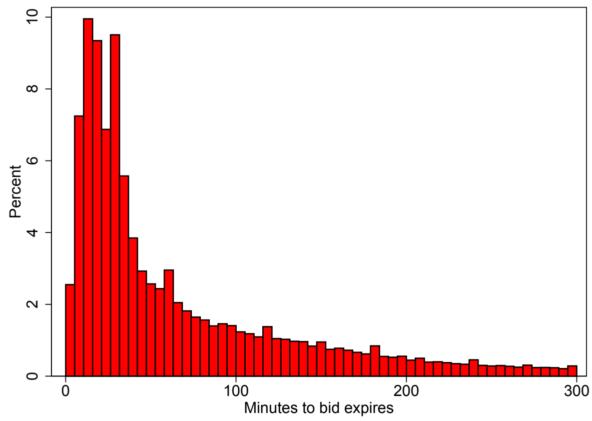
Figure B.1: Release day for online advertisement. All transactions. Norway, 2007-2015



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

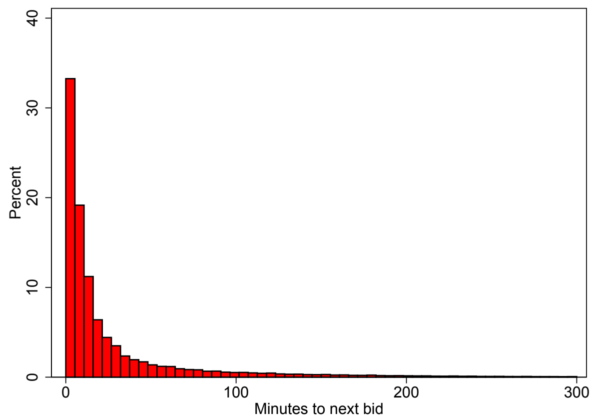
Bid expiration and time-to-next bid

Figure B.2: 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.3: 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.

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	✓	✓	✓

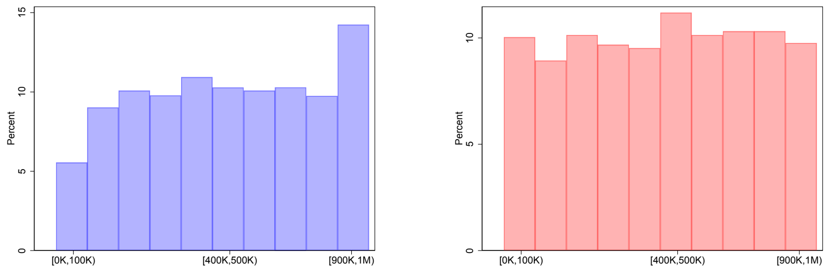
Notes: The table shows results from regressing the sell-appraisal spread on number of bidders and the distance between the opening bid and the appraisal value. The first two columns show results when only one of the variables are included, whereas the final column shows results when both variables are 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.

Appraisal validation

Figure B.4: 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.

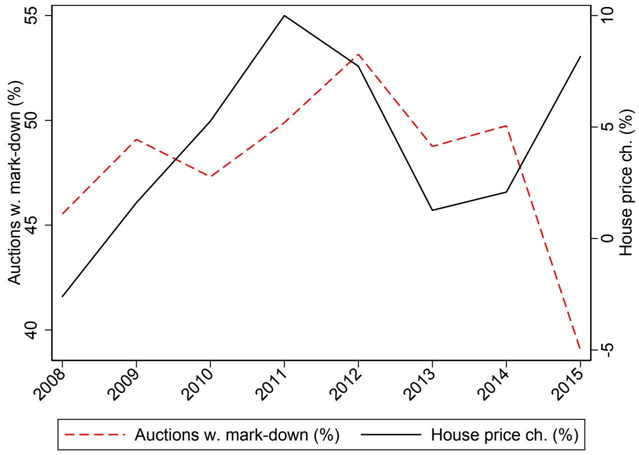
Figure B.5: Distribution of second digit (100 ths. NOK) of ask prices and appraisal values. Norway, 2007–2015



(a) Ask price (b) Appraisal value

Notes: The histogram shows the distribution of the second digit (100 ths. NOK) of the ask price (left panel) and the appraisal value (right panel). We have sliced each million-interval into 10 equally sized bins. The first bin, [0K, 100K), covers ask prices and appraisal values such as NOK 1,010,000, NOK 2,000,000, NOK 3,050,000, NOK 4,025,000, NOK 5,099,000, etc. The final bin, [900K,1M), covers ask prices and appraisal values such as NOK 1,990,000, NOK 2,900,000, NOK 3,950,000, NOK 4,925,000, NOK 5,999,000, etc.

Figure B.6: 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.

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

Table B.2: TOM and ask price. Norway, 2007–2015

	Dep. var: TOM			
Log(Ask)	0.043***	0.232***	0.032*	0.138
	(0.008)	(0.009)	(0.019)	(0.211)
Log(Common debt)			0.023***	-0.002
			(0.004)	(0.035)
Log(Size)			-1.816***	
			(0.175)	
$(\text{Log(Size)})^2$			0.154***	
			(0.013)	
No. obs.	75,384	75,161	73,026	5,448
Adj. R^2	0.000	0.143	0.186	0.240
Fixed effects:				
Year-by-month		✓	✓	✓
Zip code		✓	✓	
Construction period			✓	
Large lot			✓	
Owner type			✓	
House type			✓	
Realtor			✓	✓
Realtor office			✓	✓
Unit				✓

Notes: The table shows results from regressing TOM on the ask price. In the first column, no controls are included. In the second column, we add year-by-month fixed effects and zip-code fixed effect. In the third column, we add additional fixed effects for construction period, lot size larger than 1,000 sqm., owner type, house type, realtor, and realtor office) and a set of housing attributes. The final column report results based on a sample of units that are sold at least twice, so that we can control for unobserved heterogeneity through a regression with unit fixed effects. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

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			
	Fast sales		Slow 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.
Frac. mark-down in zip-code	0.169	0.044	-0.290	-0.191
	(0.118)	(0.526)	(0.558)	(0.572)
No. obs.	5,582	5,572	5,582	5,582
Adj. R^2	0.517	0.115	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 fraction of units within the same zip-code and sales quarter that are listed with a mark-down. 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.

Probability of sale

Table B.6: Mark-down group and the probability of sale. Norway, 2010–2015

		Dep. variable: Dummy variable equal to one if the unit is sold within 1 year. Zero otherwise			
	No. obs (%)	(1)	(2)	(3)	(4)
$\mathbb{1}$ (Mark-down < 0)	9,696	-0.432^{***}	-0.387^{***}	-0.388^{***}	-0.308^{***}
	(3.40)	(0.035)	(0.036)	(0.036)	(0.037)
$\mathbb{1}$ ($0 <$ Mark-down < 0.05)	106,441	0.214^{***}	0.165^{***}	0.151^{***}	0.040
	(36.8)	(0.024)	(0.025)	(0.025)	(0.027)
$\mathbb{1}$ (Mark-down ≥ 0.05)	21,365	-0.224^{***}	-0.278^{***}	-0.301^{***}	-0.378^{***}
	(7.4)	(0.030)	(0.031)	(0.032)	(0.034)
Constant		2.612^{***}	3.128^{***}	3.314^{***}	5.764
		(0.013)	(0.128)	(0.181)	(23.371)
Observations		288,834	288,834	288,834	288,834
Log Likelihood		−7,913.088	−7,619.642	−7,506.661	−7,248.289
Akaike Inf. Crit.		15,834.170	15,263.280	15,179.320	14,682.580
Controls:					
Hedonics			✓	✓	✓
YearMonth FE				✓	✓
County FE					✓

Notes: Data set of realtor advertised dwellings acquired from Eiendomsverdi. Time period 2010-2015. We estimate a Probit model of a listed unit being sold within 1 year. The number of observations in the default category, $\mathbb{1}$ (Mark-down $= 0$) is $151,332$ (52.3 %). The sale probability is high in all groups. The 10th percentile is 0.968 for $\mathbb{1}$ (mark-down < 0), 0.995 for $\mathbb{1}(0 <$ Mark-down $< 0.05)$, 0.979 for $\mathbb{1}$(Mark-down ≥ 0.05), in contrast to 0.989 for $\mathbb{1}$ (Mark-down $= 0$). *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

Realtor performance, strategy, and future market shares

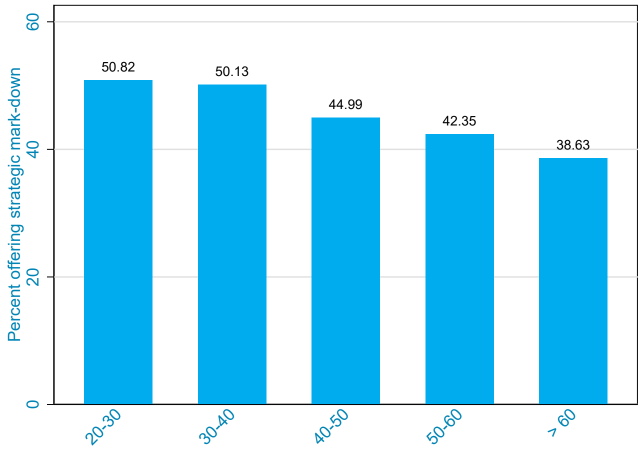
Table B.7: Change in median strategic mark-down (t-2 to t-1) among realtors and future revenue (t-1 to t). Segmentation on realtor performance. Norway, 2007–2015

	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$_{t-1}^{\text{Realtor median}}$	0.508***	0.352
	(0.207)	(0.260)
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.7: 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.

Results from estimated hedonic model

Table B.8: Selected results from the estimated hedonic model used to construct predicted prices. Norway, 2007–2015.

Independent variable: log(Sell price)	
	Sell
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.9. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

Table B.9: 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-Ask spr.
Hedonic mark-down	0.029***	-0.923***	-0.842***	0.172***
	(0.003)	(0.013)	(0.014)	(0.014)
No. obs.	7,652	7,640	7,652	7,652
Adj. R^2	0.223	0.928	0.933	0.318
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.8). 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 order to remove extreme outliers in the hedonic mark-down, we trim on the 1st and 99th percentile of the hedonic mark-down. 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.10: 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 $\geq$ 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.11: 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.

Left-digit bias

Table B.12: Left-digit bias as in Repetto and Solis. Norway, 2007-2015

	Dep. var: log(Sell)		*Dep. var: Sell-App. spread*	
	(I)	(II)	(III)	(IV)
Above threshold	-2.976***	-2.481***	-1.039	0.040
	(0.595)	(0.620)	(0.953)	(0.909)
No. obs.	23,552	22,066	15,019	14,362
Adj. R^2	0.968	0.974	0.020	0.211
Controls:				
Hedonic attributes		✓		✓
Common debt		✓		✓
Realtor FE		✓		✓
Realtor office FE		✓		✓
Year-by-month-by-Mun FE		✓		✓
Zip-code FE		✓		✓

Notes: The table report results from estimating a similar specification as in Repetto and Solis (2020). Their specification takes the following form:

$$log(sell)_i = \beta_j + \gamma \mathbb{1}\left(log(ask)_j \geq c_j\right) + \theta_j \left(log(ask)_i - c_j\right) \mathbb{1}\left(log(ask)_i \geq c_j\right) + \boldsymbol{\delta}' \boldsymbol{X}_i + \epsilon_i$$

in which c_j is the (logarithm of the) relevant round-million threshold for ask_i, β_j are threshold-specific intercepts, and $\boldsymbol{X}_i$ are a set of controls. Following Repetto and Solis (2020), we estimate this specification for all ask prices in the interval NOK 100,000 below to NOK 100,000 above the relevant threshold. We estimate this specification without any control and report results in Column (I). In Column (II), we control for log of size and the square of log size, allowing for different slope coefficients in Oslo and for apartments. The other controls are dummies for construction periods and lot size above 1,000 sqm, dummies for owner type, and dummies for house type. In addition, we include year-by-month-by-municipality fixed effects, zip-code fixed effects, realtor fixed effects, and realtor-office fixed effects. In Column (II) and Column (IV), we redo these estimations using instead the sell-appraisal spread as our dependent variable. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

Table B.13: Left-digit bias as in Repetto and Solis. Oslo, 2007-2015

	Dep. var: log(Sell) (I)	(II)	*Dep. var: Sell-App. spread* (III)	(IV)
Above threshold	-6.062***	-5.021***	-4.321**	-4.265**
	(1.615)	(1.737)	(1.863)	(1.976)
No. obs.	4,162	3,964	3,986	3,800
Adj. R^2	0.964	0.971	0.033	0.250
Controls:				
Hedonic attributes		✓		✓
Common debt		✓		✓
Realtor FE		✓		✓
Realtor office FE		✓		✓
Year-by-month FE		✓		✓
Zip-code FE		✓		✓

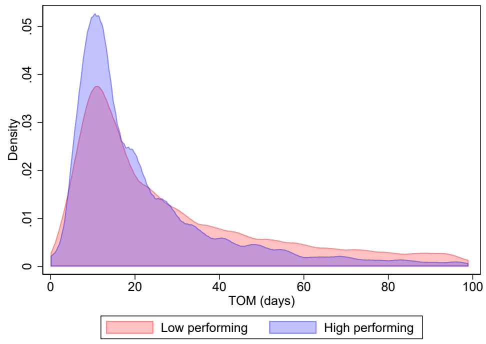
Notes: The table report results from estimating a similar specification as in Repetto and Solis (2020). Their specification takes the following form:

$$log(sell)_i = \beta_j + \gamma \mathbb{1}\left(log(ask)_j \geq c_j\right) + \theta_j \left(log(ask)_i - c_j\right) \mathbb{1}\left(log(ask)_i \geq c_j\right) + \boldsymbol{\delta}' \boldsymbol{X}_i + \epsilon_i$$

in which c_j is the (logarithm of the) relevant round-million threshold for ask_i, β_j are threshold-specific intercepts, and $\boldsymbol{X}_i$ are a set of controls. Following Repetto and Solis (2020), we estimate this specification for all ask prices in the interval NOK 100,000 below to NOK 100,000 above the relevant threshold. We estimate this specification without any control and report results in Column (I). In Column (II), we control for log of size and the square of log size, allowing for different slope coefficients in Oslo and for apartments. The other controls are dummies for construction periods and lot size above 1,000 sqm, dummies for owner type, and dummies for house type. In addition, we include year-by-month-by-municipality fixed effects, zip-code fixed effects, realtor fixed effects, and realtor-office fixed effects. In Column (II) and Column (IV), we redo these estimations using instead the sell-appraisal spread as our dependent variable. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

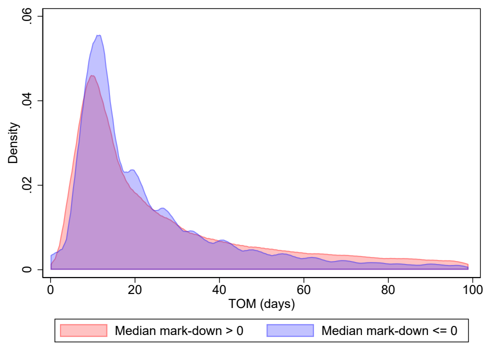
Time-on-market and realtor types

Figure B.8: Realtor performance and TOM



Notes: The figure shows the kernel density of TOM for low-performing (red) and high-performing (blue) realtors. Low-performing realtors are defined as realtor-year combinations for which the median mark-down of the realtor is lower than the 20^{th} percentile of the median mark-down of realtors in the municipality in which the agent is active. Likewise, high-performing realtors are defined as realtor-year combinations for which the median mark-down of the realtor is higher than the 80^{th} percentile of the median mark-down of realtors in the municipality in which the agent is active.

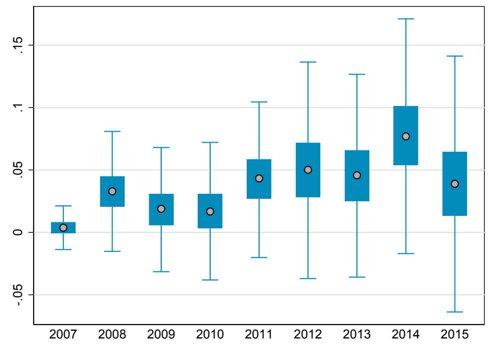
Figure B.9: Agents who typically offer a mark-down versus agents who do not typically offer a mark-down



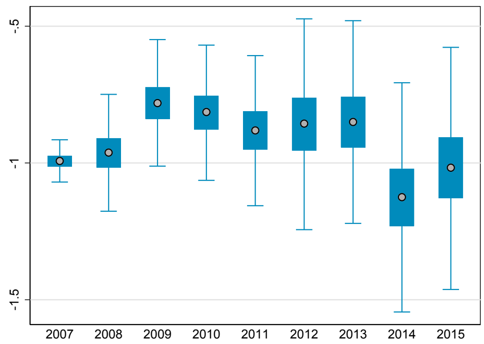
Notes: The figure shows the kernel density of TOM for agents who at the median offer a mark-down versus agents who at the median do not offer a mark-down.

Variations over the housing cycle. Norway, 2007–2015

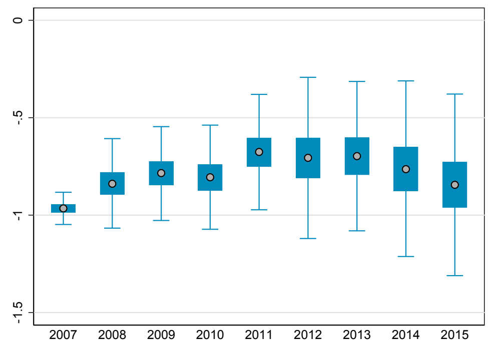
Figure B.10: Time-variation in the effect of the strategic mark-down on auction variables.



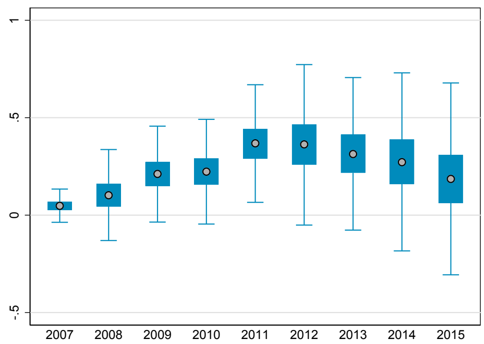
(a) No. bidders



(b) Op. bid-App. spr.



(c) Sell-App. spr.

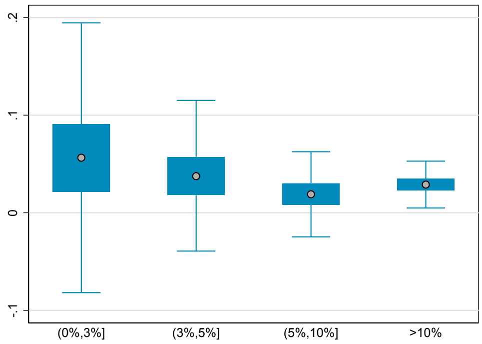


(d) Sell-Ask spr.

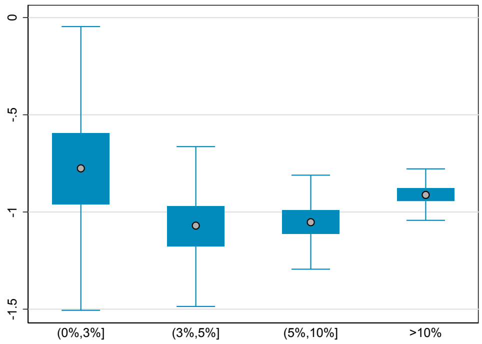
Notes: The figure shows year-specific effects of a strategic mark-down on different auction variables. Results are obtained by estimating the baseline regression models in eq. 6 year-by-year.

Non-linearities

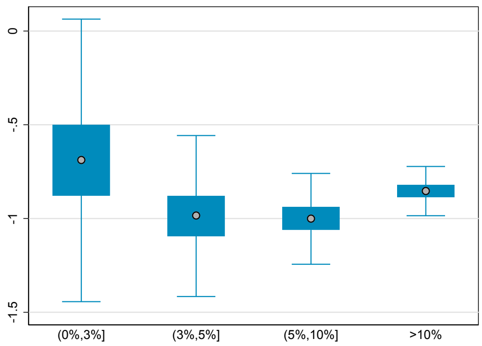
Figure B.11: Non-linear effects of strategic mark-down on auction variables. Norway, 2007–2015



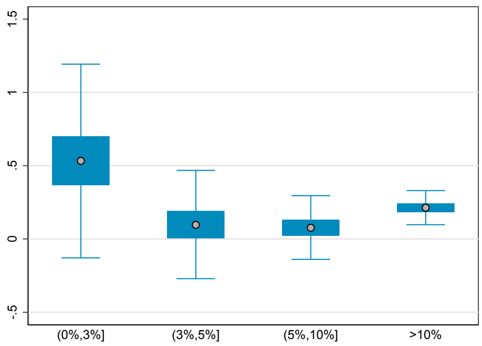
(a) No. bidders



(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.

Mark-up versus mark-down

Table B.14: Strategic mark-down versus strategic mark-up coefficients using unit fixed effects. Units sold at least twice. Norway, 2007–2015

	Dep. var: Sell-App. spread	
	(I)	(II)
Strategic mark-down	-0.904***	-0.844***
	(0.026)	(0.040)
Strategic mark-up		-0.105*
		(0.054)
No. obs.	5,582	5,582
Adj. R^2	0.751	0.752
Controls:		
Common debt	✓	✓
Appraisal	✓	✓
Realtor FE	✓	✓
Realtor office FE	✓	✓
Year-by-month FE	✓	✓
Unit FE	✓	✓

Notes: The table shows how the sell-appraisal spread is affected when the strategic mark-down is increased (lowering the ask price relative to the appraisal value) and when the strategic mark-up is increased (increasing the ask price relative to the appraisal value). The sample covers the period 2007–2015. We only consider 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.