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# Pricing and incentives in the housing market*

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**Abstract:** We study empirically the housing market effects of mark-downs, defined as having an ask price below a publicly observed estimate of a housing unit's value. Using data on repeat-sales and repeat-bids from the Norwegian housing market, we demonstrate that a positive mark-down implies more bidders, but lower opening bids. The net effect is a lower spread between the sell price and the estimated market value. Consistent with a simple model of ask price determination in the presence of a conflict of interest between the seller and realtor, we find that mark-downs are more prevalent among less experienced sellers who likely have lower bargaining power. We also find that a mark-down is associated with a compositional change in the type of bidders that bid for a housing unit.

**Keywords:** *Auctions; Bidding; Principal-agent; Strategic pricing; Directed search*
**JEL classification:** *D12; 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 to affect auction outcomes. Lower ask prices might attract more bidders, but also lower expectations of the sell price. Higher ask prices could scare away potential buyers but ensure a higher expected sell price. The role of the ask price is perhaps especially interesting when it is posted side-by-side with a value estimate, such as an appraisal value from an expert or an estimate from an automatic valuation method, because then potential buyers may use this information to form expectations on economic gains of participating in the auction. This article studies price-setting, in the particular setting of auctions for Norwegian houses. We seek to investigate price-setting by asking one main question: How does setting a relatively low ask price affect the sell price of a unit?

The short answer is that using a mark-down, i.e., setting an ask price below a value estimate that is visible to potential buyers, 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.

While the main contribution of this paper is empirical, to fix ideas, we start by developing a simple search-theory model in order to analyze price-setting when there is a conflict of interest between sellers and realtors. In the model, a seller and realtor bargain over what ask price to set, since the ask price has the function of directing potential buyers' search. A higher ask price exerts a positive direct effect on the expected sell price, given a sale, but also lowers the expected number of potential buyers that would visit and bid for the house. This indirect effect ends up lowering the expected sell price, as well as the sale probability. The conflict of interest arises from the relative impatience of realtors compared to sellers, in which case the realtor prefers a lower ask price (and a higher sell probability) compared to the seller. In this environment, we show that an ask price set by the seller-realtor pair is increasing in the bargaining strength of the seller. To the extent that more inexperienced sellers have lower bargaining power, this also leads to the prediction that the ask price is lower for more inexperienced sellers.

Our empirical analyses are based on a combination of data sets. The main data set contains a complete log of all bids in all auctions from DNB Eiendom, which is 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 800,000 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 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, in which we pose questions on the role of the ask price. The survey results corroborate our econometric results.

We use the appraisal value as our value estimate. In contrast to the situation in other countries, the appraisal value has no bearing on the mortgage a prospective buyer is granted, and is not binding for home buyers who finance their property purchase through a bank. However, an appraisal value is visible to prospective home buyers, who can use it to form expectations of the value of a unit. We show empirically that the median difference between sell prices and appraisal values, across auctions and over time, is zero. Moreover, we provide evidence that the appraisal is set independently and non-strategically from the ask price. The appraisal value may, therefore, be considered as exogenous to the ask price and function only as a useful gauge of a housing unit's value.

We investigate how an ask price that is set lower than the appraisal value affects the number of viewers at the open house, number of bidders, the opening bid, and the sell price. Since it is a natural default choice to let the ask price be equal to the appraisal value, we define a *mark-down* as having an ask price below the appraisal value. We control for unobserved unit heterogeneity in several ways. First, we control directly for the appraisal value. Second, we follow units that are sold at least twice and include unit fixed effects in our regressions. Third, we follow realtors over time, which means that our regressions include realtor and realtor-office fixed effects.

Our results point to a negative effect on the sell price from having a mark-down. Specifically, an ask price that is 1 percent below the appraisal value translates into a sell price that is 0.8 percent lower than the counterfactual sell price that would have been achieved without the mark-down. Consistent with our theoretical framework, we do find an effect on the number of bidders, but this effect seems to be dominated by the direct effect of the ask price on the sell price.

We take the analysis one step further and investigate other outcomes of the housing transaction process. First, our theoretical framework suggests that sellers and realtors may be motivated to use a mark-down to have a quicker sale. Empirically, we do find an effect on time-on-market (TOM), but the quantitative effect is small. When we use 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 remained unsold, and investigate which units have been sold or not after a year, we detect only small differences between the sale probability of units with mark-downs compared to units without 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. While estimated effects on TOM and sell probability are small, we find that younger sellers more often are involved in sales with a mark-down. This is consistent with the prediction from our theoretical model that a mark-down is more likely among inexperienced sellers, who have lower bargaining power vis-à-vis the realtor. We also follow realtors over time and classify them according to their score on a performance metric. Low performance-score realtors tend to be associated with mark-down strategies to a greater extent than high performance-score realtors. Finally, we find that a mark-down tends to attract bidders with a lower willingness-to-bid. Thus these bidders are unlikely to help push the high valuation bidders to bid closer to their valuations.

We perform several robustness checks and mention some of them here. First, units that need renovation could have an apparent mark-down and also sell at lower prices. We do not find any association between the use of a mark-down and renovation frequencies in the years prior to and after a sale. Second, within the set of mark-down strategies in the housing market, one strategy has received attention, namely 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 estimate a hedonic model as an alternative way of measuring the value of a unit, with similar results as our baseline. Fourth, we show that our results are robust to segmentation on size, price, unit type, TOM, and location. Finally, potential non-linear effects of mark-downs could arise if larger mark-downs drive the results. We do not find evidence for this.

*Related literature:* Our paper contributes to several strands 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), as an anchor for subsequent negotiations (Merlo et al. (2015)) and may serve a role in directing search (Han and Strange (2015), Albrecht et al. (2016)).

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 a mark down in the Norwegian housing market lowers the sell price but only very mildly improves TOM or the sell probability. We can go one step further than these studies and show that seller experience is associated with the prevalence of mark-downs and that sellers may be too trusting of their realtor. This is understandable, given how infrequently people sell units, and their lack of experience with this process.

We also add to the literature on bidding behavior. 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 mark-down results in a larger number of bidders. However, the direct effects associated with a lower ask price seem to dominate these indirect bidder effects, so that a 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, albeit somewhat weaker once we control for the appraisal value. Our paper, however, studies the effects of mark-downs more generally 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 this literature by showing that less skilled realtors appear to advise sellers to mark down the ask price.

Finally, our paper is related to recent work by Gilbukh and Goldsmith-Pinkham (2019), who show that realtor experience matters for the speed with which a house sells. They find that house sales mediated by more inexperienced realtors take longer to sell and especially so during housing market downturns. Moreover, they show that part of the effect comes from more experienced realtors using strategic pricing by lowering ask prices. We complement these findings by looking at another dimension of heterogeneity across realtors, namely their ability (proxied by their relative performance) and provide evidence consistent with lower ability realtors tend to engage in strategic pricing in Norway, despite this strategy having only a limited impact on selling rates. In addition to realtor experience, we also show that seller experience matters for the use of a mark-down.

The paper is structured as follows. In the next section, we describe the institutional setting of the Norwegian housing market. In Section 3, we present our model of ask price formation, the trade-offs faced when setting the ask price and the conflict of interest between the seller and realtor. In Section 4, we present the data, and discuss our empirical specification. Our main empirical results are presented in Section 5. Sensitivity and robustness checks, are discussed in Section 6. The final section concludes the paper.

# 2 Institutional background

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. Thus, after 2016 appraisal values are not commonly obtained.

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, perform water pressure checks, and inspect potential humidity problems.[1] When a unit was listed for sale, the appraisal value and the technical report were known to prospective buyers.[2] The appraisal value in our data set functions as an objective, third-party assessment of the market value of the home.

Most sales of houses and apartments in Norway are brokered by a realtor, who is hired by the seller. A realtor's remuneration typically includes a variable commission, which is proportional to the sell price and is approximately 2 percent. The length of a contract is 6 months, and the commission rate is fixed within the duration of the contract. Having obtained an estimate of the market value, the

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

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

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 an informal reflection of, 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. A seller is not legally obliged to accept a bid at, or even above, the ask price.

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.[3] The advertisement states the date of the unit's open house. 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 Fridays, there is fierce competition among sellers to attract people to their open house. Sellers may therefore use a mark-down in order to achieve this goal.

Buyers first consult with their bank in order to obtain proof of financing. The buyers document their household's income, debts, assets, and civil status. The bank assesses the financial ability of the applicant.[4] Proof of financing is generally not contingent on any particular unit – it reflects the maximum loan a buyer may obtain to finance a bid 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.

The sale of a unit takes place through an ascending-bid auction. Thus, our term "auction" should not be taken to mean forced sale, distressed sale, or any other extraordinary sale. In Norway, transactions are arranged as English auctions at the outset. Bids are placed using digital platforms, and the realtor informs the active and inactive participants of developments in the auction. All bids are legally binding, as is an acceptance of a bid. When bidders make their first bids, they typically submit proof of financing, although this practice is cloaked in some technicalities since the buyer does not want to inform the realtor of borrowing limits. 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. A more detailed account of the

[3]See Figure A.3 in Appendix A.

[4]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.

institutional background is given in Appendix A.

# 3 Theoretical Framework

In this section, we set-up a simple theoretical framework that can help rationalize our main empirical results. We consider a standard (partial equilibrium) model of ask price determination and directed housing search, in which a single seller together with her realtor try to sell a house, taking as given the search behavior of buyers (and implicitly the ask price choices of other seller-realtor pairs). In addition, there is *ex ante* seller and realtor bargaining over the ask price.

**Preliminaries.** There is a single period with four stages:

- In Stage 0, a seller-realtor pair puts a house for sale and posts an ask price $a$. We assume that the ask price is determined by Nash bargaining between the seller and realtor, where the seller has bargaining strength $\eta$.
- In Stage 1, buyers direct their search based on the ask price, $a$ (details below).
- In Stage 2, a transaction takes place, if at least one buyer has visited the house.
- In Stage 3, agents obtain payoffs.

**Payoffs.** Given at least one buyer arriving in Stage 1, the seller obtains a payoff equal to $(1 - f)\,p$, where $f$ is the realtor commission rate and $p$ is the sell price. Given no buyer arrival, the seller obtains a payoff equal to $z_S$. Therefore $z_S$ is the seller's reservation price, which reflects the value to the seller of holding the house and selling it in the future.

Given at least one buyer arriving in Stage 1, the realtor obtains a payoff of $fp$. Given no buyer arrival, the realtor obtains a payoff of $z_R$. This is the "reservation price" of the realtor, which reflects the value to the realtor from selling the house in the future.

We assume that the commission rate $f$ is exogenous and independent of the sell price $p$, ask price $a$, and the seller and realtor reservation prices. As discussed in Section 2, this is consistent with how commission rates are determined in practice in Norway, with realtors offering a commission rate at the time when the seller-realtor match is formed, which is before the determination of the ask price, and which does not change with the arrival of (new) information about the hedonic value of the house (from the appraisal) or changing market conditions that would affect the sell price.[5]

We make one important parametric assumption.

**Assumption (relative impatience):** $\frac{z_R}{f} \leq \frac{z_S}{1-f}$.

The assumption implies that – adjusting for the commission rate – realtors are relatively more impatient than sellers in the sense that their reservation price is lower than that of sellers. In directed search models this has the natural and intuitive implication that if there is a trade-off between ask (and sell) price and probability of sale, realtors would prefer to post a lower ask price to ensure a higher probability of sale compared to sellers.

The assumption is reasonable since the realtor reservation price $z_R$ is likely much lower than the seller reservation price $z_S$. First, the realtor expects to obtain a commission rate $f$ from selling the house in the future, which empirically is well below one. Second, the realtor faces effort costs while the house is on the market due to a limited capacity to mediate housing transactions. Third, there is a positive probability that the seller breaks up the relationship with the realtor and hires a different realtor, which effectively would make a realtor discount future payoffs from selling the house at a higher rate than the seller. Finally, the realtor might experience reputational damage due to not succeeding in selling the property, which additionally reduces the realtor's effective discount factor.[6]

A buyer who buys a house obtains a payoff of $u - p$, in which $u$ is the hedonic value of the house. For simplicity, we assume that a buyer who does not end up buying a house obtains a payoff of 0.[7]

**Directed search.** There is a continuum of sub-markets characterized by an ask price $a$ and tightness $\theta$. The tightness $\theta$ governs the arrival of buyers to houses, with a higher value of $\theta$ implying a higher number of buyer arrivals in expectation.

Buyers are indifferent between searching in any market segment that gives them utility level at least as large as a (exogenous) utility level $\overline{U}$. Formally, let

[5] Also, the seller and realtor reservation prices are private information for each party.

[6] In a simple dynamic extension of our framework, one can endogenize $z_R$ and show explicitly these relationships between the realtor's reservation price and deeper parameters such as the per-period search/mediation cost the realtor incurs and the realtor's discount factor. Importantly, since the commission rate is exogenous, having equally patient realtor and seller occurs only as a knife-edge case. Moreover, for values of $f$ close to 0, the realtor is more impatient than the seller.

[7] We treat buyers as ex ante homogeneous to keep our stylized model simple. The main predictions of the model would hold qualitatively if one were to assume some *ex ante* heterogeneity among buyers.

$U(a,\theta)$ be the utility level that a buyer expects *ex ante* at Stage 0 from searching in sub-market $(a,\theta)$, then

$$U(a,\theta) = \overline{U}, \tag{1}$$

among the set of submarkets that attract buyers.[8]

We assume that for the Stage 0 utility of a buyer, $U$ is decreasing in $a$ and $\theta$. Below we provide a micro-founded example that features a buyer utility with these properties. Given these properties of $U$, from Eq. (1), by the implicit function theorem, we have that we can define implicitly a function $\theta(a)$, such that

$$\frac{d\theta}{da} = \left.\frac{\partial\theta}{\partial a}\right|_{U=\overline{U}} < 0. \tag{2}$$

This is the main implication of any model of price posting and directed search: indifference by buyers between searching in different sub-markets implies that there is a negative relationship between tightness and the posted (ask) price.

**Buyer arrival (Stage 1).** We assume that the number of buyers $B$ that arrive to a house, given tightness $\theta$, is distributed as a Poisson random variable with parameter $\mu(\theta)$, where $\mu$ is increasing in $\theta$. For technical reasons, we assume that $\mu(\theta) > 1$ $\forall\theta$, so that the average number of arriving buyers is always greater than one.[9] Therefore, the probability that no buyer arrives is $\Pr\{B = 0\} = \exp\{-\mu(\theta)\}$, which is decreasing in $\mu$ and, hence, in $\theta$.

**Expected price (Stage 0).** Let $P(a,\theta)$ denote the *expected* price as of Stage 0 that a seller and realtor expect to get, conditional on sale (i.e., at least one buyer arriving in Stage 1). We assume that $P$ is increasing in $a$ and $\theta$.[10]

There are several reasons why we think the assumption that the sell price increases in the ask price, other things equal, is generally valid in the housing market. For example, this would be the case if the ask price conveys information to buyers about the quality (hedonic value) of the house. Alternatively, it can arise because in the case of a negotiated sale when only one buyer arrives, the ask price (partially) commits the seller to accept that price as the sell price. Finally, there could be behavioral reasons, whereby in an auctioned sale, when more than one

[8] In standard equilibrium competitive search environments $\overline{U}$ is pinned down as the maximum utility a buyer can achieve by searching across any sub-market (Moen, 1997). Note that buyers will never search in sub-markets with $a > u$.

[9] This is empirically relevant for the Norwegian context if one equates the number of arriving buyers to either the number of viewers or bidders.

[10] Below, we provide one possible micro-foundation (together with the micro-foundation for the buyer utility $U(a,\theta)$) that features these properties for $P$.

buyer arrives, a lower ask price leads to a lower opening bid, which influences the bidding strategies of all subsequent buyers due to anchoring effects (Tversky and Kahneman, 1974). Such anchoring effects have 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).

The assumption that the expected price is increasing in the tightness $\theta$ is equally plausible, given that a higher value of $\theta$ implies that the expected number of buyers increases. This in turn increases the probability that an auctioned sale with more than one buyer will take place and, moreover, that it is more likely that a larger number of buyers would participate in the auction, conditional on there being an auctioned sale. Both of these factors imply a higher expected price since an auction tends to deliver a higher price than a negotiated sale, and an auction with more bidders tends to deliver a higher auctioned price.

**A micro-founded example.** We provide an example of a transaction process that delivers an expected sale price $P$ and buyer expected utility $U$ with the properties described above. The example is motivated by the models in Albrecht et al. (2016) and Anundsen et al. (2022).

If only one buyer arrives (i.e., $B = 1$), we assume that the sale price equals the ask price, i.e., $p = a$, so that the seller commits to selling at the ask price.[11] If more than one buyer arrives (i.e., $B > 1$), then buyers Bertrand-compete and bid up the price up to their valuation $u$, i.e., $p = u$.

The expected price given that trade takes place is, therefore,

$$P(a, \theta) = \Pr\{B = 1 | B > 0, \theta\} a + \Pr\{B > 1 | B > 0, \theta\} u.$$

Similarly, the buyer's Stage 0 expected utility is

$$U(a, \theta) = \Pr\{B = 0 | \theta\} 0 + \Pr\{B = 1 | \theta\} (u - a) + \Pr\{B > 1 | \theta\} 0$$

or

$$U(a, \theta) = \Pr\{B = 1 | \theta\} (u - a).$$

Using the properties of the Poisson distribution, we have that

$$P(a, \theta) = \frac{\mu(\theta)}{\exp\{\mu(\theta)\} - 1} a + \left(1 - \frac{\mu(\theta)}{\exp\{\mu(\theta)\} - 1}\right) u.$$

[11] One can alternatively assume a partial commitment environment where the seller sells at $a$ only with probability $\nu$, while with probability $1 - \nu$ the seller sells at her true reservation price which – given the realtor commission fee – equals $\frac{1}{1-f} z_S$.

It follows immediately that $P$ is increasing in $a$. Also, for $a < u$, $P$ is increasing in $\mu$ and, consequently, in $\theta$. Similarly, for the buyer expected utility, we have

$$U(a,\theta) = \mu(\theta)\exp\{-\mu(\theta)\}(u-a).$$

It also immediately follows that $U$ is decreasing in $a$. Furthermore, $\mu(\theta)\exp\{-\mu(\theta)\}$ is decreasing in $\mu$ for $\mu > 1$ and, hence, given $u > a$, $U$ is decreasing in $\theta$.

Given the properties of $P(a,\theta)$ and $U(a,\theta)$ and the assumption of direct search by buyers, our model already delivers a number of predictions which we summarize next before proceeding to endogenizing the ask price.

**Prediction 1:** *The expected number of buyers that visit the house $E[B|a]$ is decreasing in the ask price $a$.*

This prediction follows directly from the directed search by buyers (c.f. Eq. (2)) and from the fact that by the Poisson assumption on buyer arrival, the expected number of buyers is increasing in the tightness $\theta$.

**Prediction 2:** *The ask price $a$ affects the expected price $P(a,\theta)$ via two effects: 1) a direct positive effect and 2) an indirect negative effect that operates through tightness $\theta$.*

This prediction follows from combining Eq. (2) with the properties of $P(a,\theta)$ and noticing that

$$\frac{dP}{da} = \underbrace{\frac{\partial P(a,\theta)}{\partial a}}_{>0} + \underbrace{\overbrace{\frac{\partial P(a,\theta)}{\partial \theta}}^{>0}\overbrace{\frac{\partial \theta}{\partial a}}^{<0}}_{<0}.$$

**Prediction 3:** *In our micro-founded example, the (expected) sell-ask spread, $(P-a)/a$, is decreasing in $a$.*

We show this prediction in Appendix D.

**Ask price determination.** Next, we examine ask price determination and show one more prediction of our model. We assume that the ask price is determined as the outcome of Nash bargaining between the seller and realtor. For simplicity, we assume that the seller and realtor's outside options are $\chi_S = \frac{z_S}{1-f}$ and $\chi_R = \frac{z_R}{f}$, respectively, which are the reservation values to each agent given an unsuccessful sale in the period.[12]

The assumption that the ask price is determined as the result of negotiations between the seller and realtor is realistic and reflects the Norwegian institutional context. Moreover, in our data, we see periods of frequent changes in the ask price, which most likely reflect negotiations between the realtor and the seller over the ask price.[13] The assumption of Nash bargaining is made for analytical convenience.

Given Nash bargaining the ask price satisfies

$$a = \arg\max_{\tilde{a},\theta} \left\{V_S\left(\tilde{a},\theta\right) - \chi_S\right\}^{\eta} \left\{V_R\left(\tilde{a},\theta\right) - \chi_R\right\}^{1-\eta} \tag{3}$$

$$s.t.\; U\left(\tilde{a},\theta\right) = \overline{U}.$$

The Stage 0 payoff of a Seller if search takes place in sub-market $(a, \theta)$ is

$$V_S\left(a,\theta\right) = \Pr\left\{B = 0|\theta\right\} z_S + \Pr\left\{B > 0|\theta\right\}\left(1 - f\right) P\left(a,\theta\right).$$

Similarly, the Stage 0 payoff of the Realtor if search takes place in sub-market $(a, \theta)$ is

$$V_R\left(a,\theta\right) = \Pr\left\{B = 0|\theta\right\} z_R + \Pr\left\{B > 0|\theta\right\} f P\left(a,\theta\right).$$

Next, we show that if realtors are relatively more impatient than sellers, so that $\chi_R < \chi_S$, then the ask price that a seller-realtor pair sets is increasing in the bargaining strength of the seller $\eta$.

**Proposition 1.** *Consider the model set-up above and suppose that $\chi_R < \chi_S$. Then the ask price a that is set by the seller-realtor pair in Stage 0 (Eq. (3)) is increasing in the seller's bargaining strength $\eta$.*

*Proof.* See Appendix D. □

The result rests on realtors being more willing to trade off a lower ask price and higher tightness to a higher ask price and lower tightness compared to sellers.[14]

[12] Therefore, we assume that if bargaining between the seller and realtor breaks down, they wait for a period before they can attempt to sell the house again. Such an assumption is standard in search models. We additionally adjust the outside option by $1 - f$ and $f$ respectively for tractability and to simplify the analysis.

[13] Such negotiations between the realtor and the seller often take place prior to the online listing, but ask price changes are still being logged in the data set, since our logs cover the period from the seller hiring a realtor until a bid is accepted and the unit is sold.

[14] In our micro-founded example, it is straightforward to modify the realtor's payoff $V_R(a, \theta)$ with an additional payoff term that is increasing in the sell-ask spread, the difference between the sale price $p$ and ask price $a$. Since in that example the sale price exceeds the ask price whenever there is more than one buyer arriving, one can show that such an additional payoff further lowers the realtor's preferred ask price.

Therefore, if realtors have all the bargaining power ($\eta = 0$) they would set an ask price that is strictly lower than the ask price that sellers would set if they had all the bargaining power ($\eta = 1$). In between, when $\eta \in (0, 1)$, Nash bargaining implies an ask price in between these two extremes. Moreover, the negotiated ask price gets closer to the seller's preferred ask price as $\eta \to 1$.

It is natural to assume that more inexperienced sellers have a lower bargaining strength. Such sellers likely have less knowledge about the incentives of realtors, or about housing market conditions, so they are more likely to let realtors "choose" the ask price. This gives us one more model prediction:

**Prediction 4:** *The ask price set by a seller-realtor pair with a more inexperienced seller in the sense of the seller having lower bargaining strength, $\eta$, is lower.*

The above 4 model predictions are made with reference to the ask price. Under the assumption that the appraisal value is fixed and pre-determined at the time of ask price determination, which given the institutional description in Section 2 and our discussion in Section 4.3 below appears valid for Norway, one can equivalently state these same predictions, with reference to the mark-down/mark-up of the ask price relative to the appraisal value.

# 4 Data and empirical approach

## 4.1 Data sets

### 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, which 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.[15] This debt is called the "common debt", and each member of the co-op is charged a monthly fee to service their share of that debt. We have data on this debt and control for it in the empirical analysis.

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

The data set consists of 133,881 auctions. We remove sales of units with an unknown address and all units transacted over 3 times.[16] 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, size, mark-down, the sell-ask spread, and the sell-appraisal spread.[17] This leaves us with 117,834 auctions, which in turn involve 810,444 bids.

Appraisal values are not reported in all cases,[18] and we are left with 74,005 auctions,[19] which involve 545,793 bids.

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

About half of the transactions have an ask price below the appraisal value. On average, an auction has about 7 viewers at the open house and a bit more than two bidders. This is true of auctions with mark-downs and auctions without mark-downs. The opening bid is typically lower than the ask price and the appraisal value for both segments. However, for units with a mark-down, the distance between the opening bid and the appraisal value is greater, indicating that a mark-down may impact the expected sell price. 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 mark-down result in a sell price that, on average, is below the appraisal value. In contrast, units with no mark-down have a positive sell-appraisal spread.

In general, units with a mark-down are smaller and cheaper, and apartments are represented more often than detached units. Use of mark-downs is observed more frequently in Oslo. In order to explore the sensitivity of our results to the

[16] Very few units have been transacted over three times using DNB Eiendom as the real estate agency each time. 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.

[17] 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.

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

[19] We use the term 'auction' here even though the term 'transaction' would be more apt for sales processes in which the TOM, and the resulting sales process entails a one-on-one negotiation between the seller and a single bidder.

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

| | Ask price < Appraisal value | | Ask price ≥ Appraisal value | |
|---|---|---|---|---|
| Variable | Mean | Std. | Mean | Std. |
| Sell (in 1,000 USD) | 433.20 | 202.58 | 419.82 | 216.83 |
| Ask (in 1,000 USD) | 422.75 | 200.46 | 408.91 | 210.13 |
| Appraisal (in 1,000 USD) | 438.14 | 208.12 | 408.41 | 210.04 |
| Square footage | 1063.60 | 548.39 | 1124.18 | 535.44 |
| Mark-down (in %) | 3.49 | 3.38 | -0.14 | 0.64 |
| Sell-App. spr. (in %) | -0.70 | 8.62 | 2.88 | 7.53 |
| Sell-Ask spr. (in %) | 2.84 | 7.57 | 2.74 | 7.53 |
| No. Interested | 7.29 | 8.60 | 6.95 | 8.05 |
| No. bidders | 2.38 | 1.62 | 2.21 | 1.44 |
| Op. bid-ask spr. (in %) | -6.65 | 6.49 | -6.70 | 6.67 |
| Op. bid-app. spr. (in %) | -9.89 | 7.29 | -6.57 | 6.69 |
| Op. bid-sell spr. (in %) | -8.95 | 6.80 | -8.90 | 6.94 |
| Perc. owner-occupied | 65.55 | | 71.46 | |
| Perc. apartment | 59.81 | | 50.37 | |
| Perc. Oslo | 32.30 | | 21.65 | |
| No. auctions | 34,298 | | 39,707 | |

**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 (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 $USD/NOK = 0.1639$.

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.

### 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 auction dynamics. While we will refer to the survey results throughout the paper, the detailed results are reported in Appendix B.

**Seller experience data**

We commissioned the data analytics firm Eiendomsverdi to map the use of mark-downs across age groups of sellers. This firm has access to seller identification and age using the public registry of owners. The resulting data set include 632,755 observed sellers in transactions in which realtors were involved and appraisal values were used. This data set spans January 1st 2003 and February 1st 2018. Each unit owner was identified, but multiple owners of the same unit are possible. Eiendomsverdi removed sellers younger than 20 years of age.

**Ask price revision data**

One challenge with our main data set is that it only contains the date at which the realtor is hired, not the actual listing date, which makes it difficult to infer TOM precisely.

For this reason, we have also collected data from DNB Eiendom for a slightly different sample period (September 2019 – December 2021). We use these data for multiple reasons. First, despite the different sample period (in which appraisal values are no longer commonly used), the data contain the actual listing date, a feature which allows us to calculate TOM directly and accurately. Furthermore, the data set contains the full history of ask price revisions, if any, including the dates at which a revision was made, together with the original ask price.

We estimate a hedonic model and use the predicted value as an estimate of the market value (replacing the appraisal value). The $R^2$ from the hedonic model is 0.823.[20]

**Failed sales data**

We have acquired data on both sold and unsold units from Eiendomsverdi. These data consist of information on units that are not transacted, thus information

[20] We trim on the $1^{st}$ and $99^{th}$ percentiles of the sell-ask spread, the sell-predicted spread, and the spread between the ask price and the predicted price. This trimming resembles the trimming done on the sell-appraisal spread and the ask-appraisal spread (mark-down) in our original data set.

cannot be found in public transaction registries.

We define unsold units as units that have been on the market for 365 days, without being sold.[21] Table C.1 in Appendix C summarizes the underlying data for unsold units across years.

**Transaction data**

Our main analysis uses bid logs and auction data from a single company, DNB Eiendom. We have, however, also accessed transaction level data from the firm Eiendomsverdi. These data cover all sales listed on the online platform Finn.no. We use these data in a robustness exercise. 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 effect on number of bidders, and the effect on the nominal value of the opening bid.

Table C.2 in Appendix C summarizes the data in a check for balance. It is evident that the data from DNB Eiendom are comparable to the full transaction data.

## 4.2 Empirical approach

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

$$y_{h,t} \in \Bigg\{ No.Viewers_{h,t}, No.Bidders_{h,t}, \frac{Opening\ bid_{h,t} - Appraisal_{h,t}}{Appraisal_{h,t}}, \frac{Sell_{h,t} - Appraisal_{h,t}}{Appraisal_{h,t}}, \frac{Sell_{h,t} - Ask_{h,t}}{Ask_{h,t}} \Bigg\}.$$

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

$$y_{h,t} = \eta_h + \alpha_t + \zeta log(Appraisal_{h,t}) + \beta \text{Mark-down}_{h,t} + Controls + \varepsilon_{h,t}, \qquad (4)$$

in which $h$ indexes the unit that is sold at time $t$ and $\alpha_t$ refers to year-by-month fixed effects. We include the appraisal value, $Appraisal_{h,t}$, to control for the price

[21] We have trimmed on the $0.1^{st}$ and $99.9^{th}$ percentiles of the sell and ask prices, and square meter price. We have also removed observations without appraisal value and trimmed on the $1^{st}$ and $99^{th}$ percentiles of the ask-appraisal spread. Finally, we trimmed by requiring that mark-downs are non-negative and no greater than ten percent.

level of the unit $h$ at time $t$ in order to isolate the mark-down effect from the price level. Moreover, including the appraisal allows us to control for unobserved heterogeneity among housing units. Our variable of interest, the mark-down, is defined as Mark-down$_{h,t} = \frac{\left(Appraisal_{h,t} - Ask_{h,t}\right)}{Appraisal_{h,t}}$. A positive value means that the ask price is below appraisal while a negative value means that the ask price is above appraisal. We consider a sub-sample that consists of units that are transacted multiple times, which allows us to control for unit fixed effects, $\eta_h$. Additionally, we control for common debt, realtor-fixed effects, and realtor-office fixed effects.

## 4.3 The exogeneity of the appraisal value

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.

### Common practice

In Norway, in the time period we study, the decision of hiring an appraiser and obtaining an appraisal value is associated with the frequency of obtaining an appraisal value at the municipality level. If we define a common practice as a situation in which at least 80 percent of transactions are observed as having the sellers make the same choice (i.e., either at least 80 percent of sellers do not obtain an appraisal value or at least 80 percent of sellers do obtain an appraisal value), we find that 93 percent of transactions are such that they adhere to what is common practice in their municipality. Thus, to a large extent, the choice of having an appraisal, or not, depends on what municipality the house is located in. We show this in a histogram in Figure C.1 in Appendix C.[22]

For municipalities in which there is no common practice, i.e., municipalities in which the frequency of obtaining an appraisal value lies between 20 and 80 percent, we estimate a hedonic model, in which we also include a dummy for appraisal value. The coefficient on the appraisal dummy has a t-value of 0.54. It therefore seems that the choice of collecting an appraisal, or not, is not associated with an effect on the sales price in itself. We get similar results if we instead estimate a hedonic model for the ask price.

[22]In fact, regressing an indicator variable that equals one if there is an appraisal on a set of municipality fixed effects, we achieve an adjusted $R^2$ of 0.759. Adding a set of hedonic controls (dummy for unit type, construction period, lot size, type of ownership, log of size and squared log of size, as well as log size and squared log size interacted with a dummy for Oslo and a dummy for apartment, increases the adjusted $R^2$ only marginally to 0.762. In other words, the common practice within the municipality is by far the most important explanatory factor for obtaining, or not, an appraisal value.

### Sell-appraisal distribution

The sell-appraisal spread is relatively symmetrically distributed around 0, with a large mass at 0.[23] This pattern is consistent with the notion that the appraisal value is an unbiased predictor of the sell price. An OLS regression of the sell price on the appraisal value yields an $R^2$ of 0.969, 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 be involved in sales with 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.[24] The $\mathrm{R}^2$ from this regression is 0.835, 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 $\mathrm{R}^2$ of only 0.017, and only 83 of the realtor-dummies (9.1%) are statistically significant at the 5% level. Pursuing a similar approach for the sell price, the $\mathrm{R}^2$ from regressing the percentage difference between the sell price and the predicted sell price on realtor fixed effects is 0.499, and 546 dummies (60%) are statistically significant at the 5% level. Thus, while realtors seem to have an important role 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 individuals 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.

In order to investigate whether a left-digit bias is present in Norway, we slice all millions of ask prices into 10 equally sized intervals, in order to study the within-million distribution (see Figure C.3 in Appendix C). The first bin covers

[23] See Figure C.2 in Appendix C.

[24] 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.

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 inspect a similar distribution of appraisal values. The distribution of appraisal values is approximately uniform, and does not exhibit a similar pattern of discontinuity as we observed in the ask price distribution, which is consistent with the proposition that appraisal values reflect the market value of the unit and are not set strategically around certain numerical intervals.

**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 mark-downs when house prices are rising, simply because the ask price is set after the appraisal value and thus would be higher as market prices increased. 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 would 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 mark-downs in a rising market than in a falling market.[25]

# 5 Empirical results

## 5.1 Baseline results controlling for time-invariant unit characteristics

In order to control for unobserved unit heterogeneity, we control for unit fixed effects. Our data contain 2,577 units that have been sold at least twice. Table 2 tabulates results based on estimating Eq. (4) for different outcome variables.

We find the coefficient on the mark-down to be 0.117 when the dependent variable is the number of viewers. The interpretation is that a 10 percentage point increase in the mark-down would attract 1.12 more viewers. The coefficient on number of bidders is much smaller (0.038), implying that a 10 percentage point increase in the mark-down is associated with 0.38 more bidders – approximately

[25] See Figure C.4 in Appendix C for details.

**Table 2: Mark-down coefficient for selected outcome variables using unit fixed effects. Units sold at least twice. Norway, 2007–2015**

| | *Outcome variable:* | | | | |
|---|---|---|---|---|---|
| | No. Interested | No. bidders | Op.bid-App. spr. | Sell-App. spr. | Sell-Ask. spr. |
| Mark-down | 0.117*** | 0.038*** | -0.908*** | -0.804*** | 0.224*** |
| | (0.037) | (0.011) | (0.052) | (0.052) | (0.054) |
| No. obs. | 5,121 | 5,121 | 5,121 | 5,121 | 5,121 |
| Adj. $R^2$ | 0.477 | 0.222 | 0.265 | 0.430 | 0.315 |
| *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 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. Standard errors are clustered at the zip-code level. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

one third of the viewers end up bidding for the unit.[26] While the quantitative effect on number of bidders is small, our results suggest a larger effect than what Han and Strange (2016) find on US data. They find that lowering the ask price by 10 percent is associated with a 2.2 percent increase in the number of bidders. The average number of bidders in their sample is 1.73 per auction, implying an increase of roughly 0.04 bidders when evaluated at the mean. Compared to this, our estimate is significantly higher.

In the third column, we estimate the impact of a mark-down on the opening bid-appraisal spread. The coefficient estimate is -0.908. The interpretation is that a 1 percentage point larger mark-down is associated with a 0.908 percentage point reduction of the opening bid-appraisal spread.

The coefficient estimate of the sell-appraisal spread is -0.804, and the estimate is statistically significant. The interpretation is that a 1 percentage point increase

[26] We have also estimated a negative binomial, following Han and Strange (2016), for the number of bidders and viewers. The quantitative results are comparable in that case.

in the mark-down is associated with a 0.804 percentage point reduction in the sell-appraisal spread. The coefficient estimate of the sell-ask spread is 0.224, and is statistically significant. This suggests that an increase in the mark-down is associated with an increase in the sell-ask spread.

The results in Table 2 can be related to Predictions 1-3 from our simple theoretical framework from Section 3. A lower ask price (larger mark down) is associated with a higher number of bidders, which is consistent with Prediction 1 from the model. Similarly, a lower ask price (larger mark down) is associated with a higher sell-ask spread, which is consistent with Prediction 3. Third, if one interprets the "opening bid" effect as (proportional to) the direct effect of the ask price on the expected sell price (c.f. Prediction 2), the combined results of a lower "opening bid" effect, and that the overall effect on the sell price being lower in magnitude than the "opening bid" effect, are consistent with the countervailing indirect effect of the ask price through the number of buyers.

## 5.2 Other outcomes

**Time-on-market**

Our results suggest that there is a negative association between the use of a mark-down and the sell price. While sellers surely are incentivized to sell at a high price, they can also be motivated by a fast sale.

To address this issue, we use the additional data on ask price revisions from DNB Eiendom. We regress TOM on the percentage difference between the ask price and the predicted value (as an alternative way of measuring the mark-down). We control for log of common debt, log of the predicted price, year-by-month fixed effects, realtor fixed effects, and realtor-office fixed effects.[27]

Results are shown in the first column of Table 3. We find that a mark-down is associated with a lower TOM, but the effect is small. An increase in the mark-down of 1 percentage point is associated with a 0.04 days reduction in TOM. Therefore, the link between the ask price and TOM is weaker in Norway than what is found in other countries.[28] Note that TOM is very short in Norway, and

[27]We cannot control for unit fixed effects since very few properties are sold twice by DNB Eiendom over this shorter time period.

[28]To understand this discrepancy, we turn to our theoretical framework. In our model the probability of sale is $\Pr\{B>0|\theta\}$. In a dynamic model, average time-on-market $TOM$ is one over the sale probability, i.e. $1/\Pr\{B>0|\theta\}$. In Appendix D, we show that in the context of our micro-founded example from Section 3,

$$\frac{\partial TOM}{\partial a} = TOM\frac{\varepsilon_{\Pr\{B>0\},\theta}}{\left|\varepsilon_{\Pr\{B=1\},\theta}\right|}\frac{1}{u-a},$$

where $\varepsilon_{B>0,\theta}$ is the elasticity of $\Pr\{B>0\}$ with respect to $\theta$, and similarly for $\varepsilon_{\Pr\{B=1\},\theta}$. This most units sell within 21 days. In fact, only three percent of the units take 100 days or more to sell. Given the liquidity of the market, it may be hard to affect TOM by strategically changing the ask price.[29]

We have also constructed a sub-sample of units that have one or fewer ask price revisions (about 2.4 percent of the units have more than one revision). For us to classify a change in ask price as an ask price revision, we require that it takes at least 7 days from one ask price to the next ask price is posted.[30] In the sub-sample of units that are revised at most once, i.e., none or one revision, 89 percent have no revision while 11 percent of the units have an ask price revision.

For units that are observed with what we classify as an ask price revision, we recalculate TOM to be the number of days elapsed between the revision date and the sales date. We then redo the regression of TOM on the spread between the (final) ask price and the predicted price using the adjusted TOM as our dependent variable. While this adjustment increases the coefficient on the mark-down somewhat (see the second column), we still find a moderate effect.

Finally, we look at the case in which TOM is non-adjusted (sell date less initial listing date), but in which we employ our technique of re-defining the mark-down to be the spread between the initial ask price and the predicted price. Again, the coefficient is somewhat larger than in the non-adjusted case, but the estimated effect is small (final column in Table 3).

**Sell probability**

One reason for offering a mark-down could be that the seller wants to reduce the chance of a failed sale. To explore this possibility, we have acquired data on both sold and unsold units from Eiendomsverdi.

In our empirical model, we differentiate between different mark-down intervals by including dummy variables for each interval. We also include the interaction of these dummies with the mark-down. Our default category is no mark-down, and the other categories that we consider are: Mark-downs greater than zero and less than or equal to three percent; mark-downs greater than three and less than or equal to five percent; and mark-downs greater than five percent.

derivative is positive and is larger the larger is TOM, the larger is the elasticity of the sale probability with respect to $\theta$, the smaller is the elasticity of negotiated sale with respect to $\theta$ and the smaller is the surplus a buyer gets from a negotiated sale. Therefore, one natural explanation for why the estimated gradient between TOM and ask price is smaller for Norway is that TOM is lower in Norway.

[29] See also the histograms summarized in Figure C.5 in Appendix C.

[30] We implement this requirement because, as mentioned in Section 3, other more frequent changes in the ask price most likely reflect negotiations between the realtor and the seller, and not active ask price changes intended to affect the sales process.

**Table 3: Hedonic mark-down coefficient for TOM. Data with ask price revisions. Norway, 2019–2021.**

| | *Outcome variable:* | | |
|---|---|---|---|
| | TOM | Adj. TOM | TOM, adj. mark-down |
| Hedonic mark-down | -0.038*** | -0.054*** | -0.064*** |
| | (0.011) | (0.009) | (0.011) |
| No. obs. | 33,304 | 32,493 | 32,493 |
| Adj. $R^2$ | 0.080 | 0.094 | 0.085 |
| *Controls:* | | | |
| Common debt | ✓ | ✓ | ✓ |
| Predicted | ✓ | ✓ | ✓ |
| Realtor FE | ✓ | ✓ | ✓ |
| Realtor office FE | ✓ | ✓ | ✓ |
| Year-by-month FE | ✓ | ✓ | ✓ |

**Notes:** The table shows how TOM is affected when the hedonic mark-down is increased (lowering the ask price relative to a value estimate based on a hedonic model). The sample covers the period 2019–2021. In the first column, TOM is measured as the number of days elapsed between the initial listing date and the sell date and the ask price is the final ask price. In the second column, we recalculate TOM to be the number of days elapsed between the last ask price revision date and the sales date, while the ask price is the final ask price. In the final column, we calculate TOM to be the number of days elapsed between the initial listing and the sales date, while we use the initial ask price instead of the final ask price. We control for common debt and the hedonic prediction, realtor fixed effects, realtor office fixed effects, and year-by-month fixed effects. Standard errors are clustered at the zip-code level. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

We first estimate a specification without controls. We then control for the logarithm of the appraisal value, and we include year-by-month fixed effects and zip-code fixed effects. We calculate the average marginal effects of the different mark-down categories. Results are shown in Table 4. Results show that mark-downs are associated with a lower probability of a failed sale in all categories, but we only find statistically significant results for small mark-downs. The estimated effect is largest for mark-downs between 3-5 percent. In conclusion, there is some evidence in our data suggesting that mark-downs lower the probability of a failed sale.

Guren (2018) uses data in which 416,373 listings lead to 310,758 transactions. These numbers imply that 25 percent of listings did not lead to a sale. In Norway, the similar frequency was between 3 and 6 percent during the 2012-2015 period in the data set we have access to. This difference between the U.S. and Norway is notable and future research may establish the explanatory factors. We suggest that a list of possible explanatory factors would include a) financial innovation: intermediary financing makes it possible for most households to buy before selling and thus for an interim period own two houses. This ends up pushing up the steady state buyer-to-seller ratio and thus increase the sale probability (Moen et al. (2021)), b) preference and attribute homogeneity might allow higher matching probability (a small country would imply less preference heterogeneity and attribute variation as long as this effect is stronger than the opposing force of smaller market size and market thinness) c) digitization (listings often include 50 pictures of the unit, implying that buyers are close to being fully informed), d) the legal system (the law requires full disclosure of unit condition and failure entails future legal responsibility), e) institutional details around the housing transaction that may help coordinate potential buyers to bid in an auction format rather than search and bid in a less coordinated way over a long period of time.

**Table 4: Probability of failed sale. Oslo, 2012–2015**

| | Dep. variable: Dummy variable equal to one if it is a failed sale. | |
|---|---|---|
| | (I) | (II) |
| Mark-down 0-3 percent | -0.011*** | -0.009*** |
| | (0.003) | (0.003) |
| Mark-down 3-5 percent | -0.025 | -0.014 |
| | (0.028) | (0.021) |
| Mark-down 5-10 percent | -0.019 | -0.006 |
| | (0.021) | (0.014) |
| No. obs. | 67,668 | 66,013 |
| Pseudo $R^2$ | 0.015 | 0.107 |
| *Controls:* | | |
| Appraisal | ✗ | ✓ |
| Year-by-month FE | ✗ | ✓ |
| Zip-code FE | ✗ | ✓ |

**Notes:** The table shows how the probability of a failed sale is affected by offering a mark-down. A failed sale is defined as a unit that was on the market for 365 days, without being sold. We estimate a logit model and report average marginal effects. We differentiate between different mark-down intervals by including dummy variables for each interval. We also include the interaction of these dummies with the mark-down. Mark-down 0-3 percent refers to mark-downs greater than zero and less than, or equal to, three percent; Mark-down 3-5 percent refers to mark-downs greater than three and less than, or equal, to five percent; while Mark-down 5-10 percent is mark-downs greater than five and less than, or equal, to ten percent. The first column shows average marginal effects when no controls are included. In the second column, we control for the logarithm of the appraisal value, and we include year-by-month fixed effects and zip-code fixed effects. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

**Realtor incentives**

Our results indicate that a mark-down is 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 is often used 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 B.1a in Appendix B), 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 B.1b in Appendix B, respondents tend to believe that the realtor is instrumental to achieving the sell price.[31]

In order to investigate whether different realtors advise different strategies, we compare how the propensity to use a mark-down is related to realtor performance, which is computed based on the relative performance in terms of a realtor's mean sell-appraisal spread.

To this end, 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 $\theta$. The set of realtor types, $\Theta$ 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

[31] 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 0.499, and 546 dummies (60%) are statistically significant at the 5% level.

of using a mark-down, we estimate the following logit specification:

$$P[Ask_{h,t,r} < Appraisal_{h,t,r}] = \frac{e^{\beta_{FE}+\gamma'\theta_{h,t,r}}}{1+e^{\beta_{FE}+\gamma'\theta_{h,t,r}}}, \tag{5}$$

in which $\theta_{h,t,r}$ represents the realtor type $\theta$ 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. $\gamma$ 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 mark-down across the 1,000 draws are summarized for each of the five categories of realtor type in Figure 1.

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

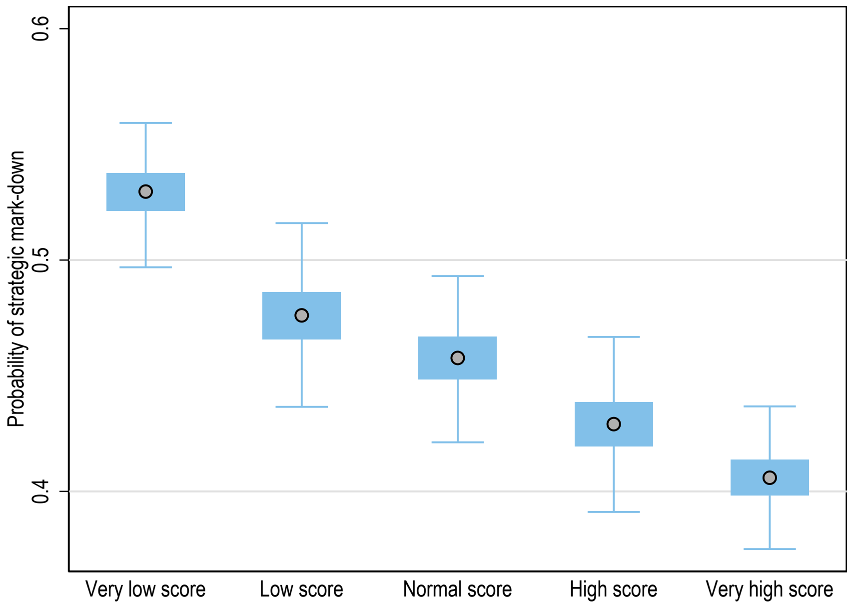
We have also investigated how the size of the mark-down is related to a realtor's performance score. To investigate this, we regressed the mark-down on dummies for each of the performance score categories. Results suggest that less skilled realtors offer larger mark-downs than more skilled realtors, a finding that supports the notion that a mark-down strategy is more widespread among lower performing realtors.[32]

#### Inexperienced sellers

Our results suggest that a 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 mark-down. These findings raise the question of whether sellers realize that mark-downs are associated with low sell prices. Since typical holding times can be periods of multiple years, most households 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 2, we plot the frequency of sales with a mark-down across different age groups based on a data set compiled by the bank-owned analytics firm, Eiendomsverdi. This figure

[32]See table C.3 in Appendix C for details.

**Figure 1: Realtor score on performance and propensity to offer a mark-down. Norway, 2007–2015**



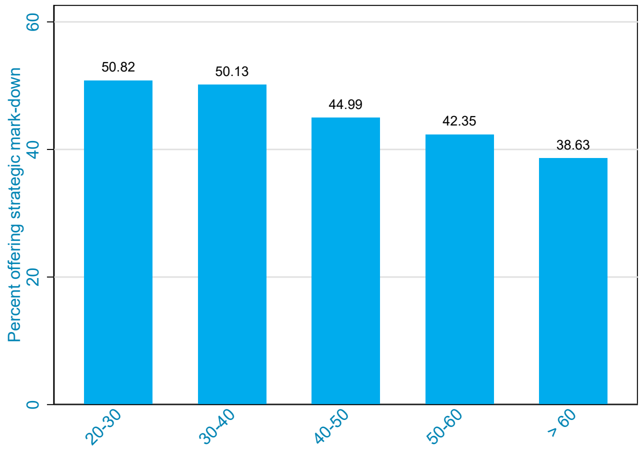

**Notes:** The figure shows box plots of the estimated probability of being involved with sales with a mark-down among different types of realtors. For each realtor and each year, we split the sample in two, randomly. Then samples are collected across years for each realtor. In each part, realtors are 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 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.

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 younger sellers being more keen to heed mark-down advice from realtors. It is also consistent with an element of learning among sellers. The association between seller experience and the use of low ask prices is consistent with Prediction 4 of our theoretical framework in Section 3.

### Composition of bidders

Our results suggest a modest effect on number of bidders from offering a mark-down. This is consistent with the finding that a mark-down exercise a negative

**Figure 2: Frequency of 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.

effect on the sell price. One reason for the moderate effect on number of bidders could be that a mark-down is associated with a compositional change in bidder type. People typically select certain price intervals for the ask price when they search for houses (see e.g. Piazzesi et al. (2020)), which could involve two opposing effects of lowering the ask price. One the one hand, a lower ask price implies that the seller targets households that would not have been interested had the ask price been higher (because the unit would have fallen on the north of the search interval and would have been considered "too expensive" for many prospective buyers). On the other hand, the seller misses households that search in a higher price interval, since a lower ask price may put the unit in the "too cheap" bucket for some prospective buyers, i.e., the unit falls south of this search interval.

To explore the possibility that a mark-down strategy affects bidder composition, we construct a new buyer category and define "final bidders" as bidders that have a maximum bid that is at, or above, the appraisal value. Our idea is that these bidders most likely would have participated in the auction also in the counterfactual situation in which the ask price had been higher. "Non-final bidders" are bidders that place a highest bid that is below the appraisal value. Our conjecture is that these bidders would have been less inclined to participate in the counter-factual situation in which the ask price had been set at a higher level.

We then examine how the two bidder types are affected by a mark-down. We find that a mark-down results in fewer final bidders, but more non-final bidders. This may help us understand the relatively small effect that characterizes the association between the mark-down and the number of bidders since the mark-down is associated with a compositional change in the type of bidders that the seller attracts. Detailed results are shown in Table 5.

**Table 5: Mark-down coefficient for different type of bidders. Units sold at least twice. Norway, 2007–2015**

| | *Outcome variable:* | | |
|---|---|---|---|
| | No. bidders | No. bidders above appraisal | No. bidders below appraisal |
| Mark-down | 0.038*** | -0.053*** | 0.091*** |
| | (0.011) | (0.012) | (0.008) |
| No. obs. | 5,121 | 5,121 | 5,121 |
| Adj. $R^2$ | 0.222 | 0.267 | 0.209 |
| *Controls:* | | | |
| Common debt | ✓ | ✓ | ✓ |
| Appraisal | ✓ | ✓ | ✓ |
| Realtor FE | ✓ | ✓ | ✓ |
| Realtor office FE | ✓ | ✓ | ✓ |
| Year-by-month FE | ✓ | ✓ | ✓ |
| Unit FE | ✓ | ✓ | ✓ |

**Notes:** The table shows how the composition of bidders is affected when the mark-down is increased (lowering the ask price relative to the appraisal value). We report the effect from no segemention (first column), which is similar to our baseline results in Table 3. In addition, we distinguish between the number of bidders who bid at, or above, the appraisal value (second column) and the number of bidders who bid below the appraisal value (third column). 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. Standard errors are clustered at the zip-code level. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

### Bidder strategies

We have also investigated how bidding behavior may be affected by a mark-down by making more use of the depth of the bidding data. For each losing bidder, we calculate the spread between their highest bid and the appraisal value. We then start by looking at how this spread is related to a mark-down using the same empirical setup as in the other analyses, i.e., we follow repeat sales while controlling for unit fixed effects. We find that losing bidders place lower max bids when there is a mark-down (first column of Table 6).

Then, we follow the same bidders across auctions and explore whether their highest bid is affected by whether the unit was listed with a mark-down or not. We do not have a sufficient amount of data on units that are sold twice with repeat bidders to control for both unit and bidder fixed effects, so we remove the unit fixed effects from this specification. Instead, we control for attributes of the unit (size, zip-code, unit type, etc.) and add bidder fixed effects. We find that bidders extend lower max bids in auctions that involve a mark-down. This finding supports the notion that the seller attracts more low willingness-to-pay bidders when she advertises the unit with a mark-down. Detailed estimation results are shown in Table 6.

# 6 Robustness and sensitivity checks

## 6.1 Unobserved heterogeneity

**Time-varying unit characteristics:**

Since the appraisal value involves an appraiser, who may make mistakes, some appraisal values may be set too high relative to the underlying market value, others too low. The former may appear as a mark-down, even if the ask price simply reflects the latent market value.

A high appraisal value relative to the underlying market 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 by including a unit fixed effect. 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.[33] In order to explore whether there is a difference in renovation frequency between the group of units with a mark-down and the group of units with an ask price that is higher than the appraisal value, we look at changes in renovation frequencies in the years preceding and following the sales year.

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

**Table 6: Mark-down coefficient for non-winning bidders' max bid. Units sold at least twice. Norway, 2007–2015**

| | *Outcome variable: Spread between highest bid and appraisal value* | |
|---|---|---|
| | Within auction | Across auctions |
| Mark-down | -0.819*** | -0.882*** |
| | (0.085) | (0.076) |
| No. obs. | 5,123 | 6,387 |
| Adj. $R^2$ | 0.318 | 0.434 |
| *Controls:* | | |
| Common debt | ✓ | ✓ |
| Appraisal | ✓ | ✓ |
| Realtor FE | ✓ | ✓ |
| Realtor office FE | ✓ | ✓ |
| Year-by-month FE | ✓ | ✓ |
| Hedonics | ✗ | ✓ |
| Unit FE | ✓ | ✗ |
| Bidder FE | ✗ | ✓ |

**Notes:** The table shows how the highest bid among non-winning auction-participants is associated with mark-downs (lowering the ask price relative to the appraisal value). In the first column, we follow all non-winning bidders within all auctions. In this case, we only consider units that are sold at least twice in order to control for unobserved heterogeneity through regressions with unit fixed effects. In the second column, we follow bidders who have lost across multiple auctions. We only consider bidders who have had a non-winning bid in at least two auctions, which allow us to control for bidder fixed effects. Since we cannot control for unit fixed effects in this case, we also add controls for log size, squared log size, noth un-interacted, and interacted with dummies for apartments and also. Additionally, we add house type FE, zip-code, owner type FE, lot size FE, construction period FE, and zip code FE. The sample covers the period 2007–2015. In both specifications, we control for common debt, the appraisal value, realtor fixed effects, realtor office fixed effects, and year-by-month fixed effects. Standard errors are clustered at the zip-code level. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

We find 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. Detailed results are shown in Table C.4 in Appendix C.

**Unobserved seller heterogeneity**

It is possible to raise the concern that a mark-down 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 mark-down and accept a low bid too soon. In this event, the impatient seller is involved in a sale with a 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 could bias our results towards magnifying the negative effect of a mark-down on the sell price.

This seller heterogeneity is connected to our previous discussion of TOM and failed sale, but we broaden our search here by dealing with the 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 mark-down and a tendency to accept low bids implies an association between a 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.

We have also explored how the likelihood of expiration bids is affected by a mark-down. We have therefore identified auctions in which at least one bid has expired before the unit was sold. In these auctions, the seller has decided to 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 a positive association between the probability of an expiration bid and a mark-down, i.e., there is little evidence supporting the notion that sellers offering a mark-down are more impatient.[34]

Finally, we experimented with an instrumental variable approach in order to control for latent seller types. As instrument we used the fraction of units within the same zip-code and sales quarter that are listed with a mark-down, 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. The results of the instrumental variable approach are similar to our baseline results. Details are shown in Table C.6 in Appendix C.

[34] The results are summarized in Table C.5 in Appendix C.

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

The summary statistics in Table 1 show that units listed with a mark-down tend to be smaller and have a higher appraisal value. Apartments are represented more often among the sample of units with a mark-down. Low ask price units are sold more frequently in Oslo.

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 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.[35] 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 C.7 in Appendix C.

## 6.3 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 of 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 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, the 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

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

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 C.8 in Appendix C. The results of our re-estimation of the regressions for auction outcomes on the mark-down when the appraisal value is replaced by the model-predicted price are presented in Table C.9 in Appendix C. The results are robust to this alternative approach.

## 6.4 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 and composition effects in the type of units, clients, and geographical areas 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.

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 C.10 in Appendix C.

## 6.5 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 C.3 in Appendix C). 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.

Results are reported in the first two columns of Table C.11 in Appendix C. 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

C.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 C.14, 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, which suggests that the finding of Repetto and Solis (2020) also have some relevance in Norway, at least in a liquid market like Oslo.

## 6.6 Variations over the housing cycle

In order to explore the sensitivity of our baseline results on auction outcomes to variations over time, we estimate (4) 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 C.6 in Appendix C. Although the effects on the number of bidders have been estimated less precisely, all of our findings are broadly robust to this exercise.

## 6.7 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 C.7 in Appendix C. The pattern is intact.

## 6.8 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 (4) 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 C.13. 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, mark-downs are associated with weak effect on the sale probability or TOM. However, we have found evidence that a mark-up is associated with a higher TOM. This is consistent with the findings in Guren (2018) and Andersen et al. (2019).

### 6.9 Right-tailed sell-appraisal distribution

When we inspect the sell-appraisal spread distribution, we observe that it has a median of zero, but a mean of 1.22, which is related to the thick right tail of the distribution.

When we zoom in on the sell-appraisal spread interval between -10 and 10 percent, the distribution has a median of 0 and the mean is -0.12 (see Figure C.8 in Appendix C).

The reason for the shift of position for the mean compared to the median is that when we remove the tails of the distribution, we remove the effect of the thicker right tail. Moreover, one explanation for the thick right tail is that sellers will decline bids that are very low compared to the appraisal value, but they will gladly accept bids that are very high compared to the appraisal value.

To explore the sensitivity of our results with respect to the right-tailed sell-appraisal spread distribution, we have trimmed away spreads falling outside the [-10,10] interval. Results are very similar to our baseline results. Please see Table C.14 in Appendix C for details.

## 7 Conclusion

We study price setting and incentives in the housing market and ask one main question: How does setting a relatively low ask price affect the sell price of a unit?

We use a simple theoretical model of ask price determination with price posting and directed search, which, among other things, shows that a lower ask price has two countervailing effects on expected prices: a positive direct effect and a negative indirect effect through tightness and the average number of buyers/bidders visiting a house. Which effect is stronger is ultimately an empirical question. This article shows empirically that a mark-down is associated with a reduction of the sell price while a mark-down is not associated with substantial effects on the time-on-market or probability of failed sale (although small effects in the expected direction can be seen). The article then proposes and investigates multiple explanatory factors in order to explain why some sellers still use the strategy.

Our explanation for why some sellers still use this strategy rests on seller inexperience and a conflict of interest between sellers and realtors over the ask price. As we show in our theoretical framework, if more inexperienced sellers have weaker bargaining strength, then that tends to lead to a lower ask price since realtors are more willing to trade-off a lower ask price for a higher sale probability. The importance of seller experience is supported by our empirical investigation.

Our findings suggest that at least in the context of Norway a rethink of the regulation of the seller-realtor contracting relation may be warranted. One important friction that leads to the conflict of interest between the seller and realtor is the practice of setting the commission rate well in advance of the actual marketing of the housing unit and keeping it fixed for multiple months, without the possibility to update it when relevant information arrives about the marketing conditions. Instead a more flexible approach to contracting between the seller and realtor, including the possibility of writing contracts with more flexible commissions may be warranted to help with better alignment of incentives.

# References


Agarwal, S., J. He, T. F. Sing, and C. Song (2019). Do real estate agents have information advantages in housing markets? *Journal of Financial Economics 134*(3), 715–735.

Albrecht, J., P. A. Gautier, and S. Vroman (2016). Directed search in the housing market. *Review of Economic Dynamics 19*, 218–231.

Andersen, S., C. Badarinza, L. Liu, J. Marx, and T. Ramadorai (2019). Reference dependence in the housing market. CEPR Discussion Papers 14147, C.E.P.R.

Anundsen, A. K., A. Lyshol, N. P., and E. Røed Larsen (2022). Match quality and house price dispersion: evidence from norwegian housing auctions. Technical report.

Anundsen, A. K. and E. Røed Larsen (2018). Testing for micro efficiency in the housing market. *International Economic Review 59*(4), 2133–2162.

Backus, M., T. Blake, and S. Tadelis (2019). On the Empirical Content of Cheap-Talk Signaling: An Application to Bargaining. *Journal of Political Economy 127*(4), 1599–1628.

Bajari, P., J. C. Fruehwirth, K. I. Kim, and C. Timmins (2012). A Rational Expectations Approach to Hedonic Price Regressions with Time-Varying Unobserved Product Attributees: The Price of Pollution. *American Economic Review 102*(5), 1898–1926.

Barwick, P. J., P. A. Pathak, and M. Wong (2017). Conflicts of interest and steering in residential brokerage. *American Economic Journal: Applied Economics 9*(3), 191–222.

Beggs, A. and K. Graddy (2009). Anchoring effects: Evidence from art auctions. *American Economic Review 99*(3), 1027–1039.

Beracha, E. and M. J. Seiler (2014). The effect of listing price strategy on transaction selling prices. *Journal of Real Estate Finance and Economics 49*(2), 237 – 255.

Bucchianeri, G. W. and J. A. Minson (2013). A homeowner's dilemma: Anchoring in residential real estate transactions. *Journal of Economic Behavior & Organization 89*, 76–92.

Cropper, M. L., L. B. Deck, and K. E. McConnell (1988). On the choice of functional form for hedonic price functions. *The Review of Economics and Statistics 70*(4), 668–675.

Einav, L., T. Kuchler, J. Levin, and N. Sundaresan (2015). Assessing sale strategies in online markets using matched listings. *American Economic Journal: Microeconomics 7*(2).

Gilbukh, S. and P. Goldsmith-Pinkham (2019). Heterogeneous real estate agents and the housing cycle.

Glower, M., D. R. Haurin, and P. H. Hendershott (1998). Selling time and selling price: The influence of seller motivation. *Real estate economics 26*(4), 719–740.

Guren, A. M. (2018). House price momentum and strategic complementarity. *Journal of Political Economy 126*(3), 1172–1218.

Han, L. and W. Strange (2016). What is the role of the asking price for a house? *Journal of Urban Economics 93*, 115–130.

Han, L. and W. C. Strange (2015). The microstructure of housing markets: Search, bargaining, and brokerage. In H. J. V. Duranton, G. and W. Strange (Eds.), *Handbook of Regional and Urban Economics, vol. 5*, pp. 813–886. North-Holland.

Haurin, D., S. McGreal, A. Adair, L. Brown, and J. R. Webb (2013). List price and sales prices of residential properties during booms and busts. *Journal of Housing Economics 22*(1), 1–10.

Herrin, W., E., J. R. Knight, and C. F. Sirmans (2004). Price cutting behavior in residential markets. *Journal of Housing Economics 13*(3), 195–207.

Horowitz, J. L. (1992). The role of the list price in housing markets: Theory and an econometric model. *Journal of Applied Econometrics 7*, 115–129.

Knight, J. R. (2002). Listing price, time on market, and ultimate selling price: Causes and effects of listing price changes. *Real estate economics 30*(2), 213–237.

Ku, G., A. D. Galinsky, and J. Murnighan (2006). Starting low but ending high: A reversal of the anchoring effect in auctions. *Journal of Personality and Social Psychology 90*(6), 975–986.

Levitt, S. D. and C. Syverson (2008). Market distortions when agents are better informed: The value of information in real estate transactions. *Quarterly Journal of Economics XC*(4), 599–611.

Merlo, A., F. Ortalo-Magne, and J. Rust (2015). The home selling problem: theory and evidence. *International Economic Review 56*(2), 457–484.

Moen, E. R. (1997). Competitive search equilibrium. *Journal of political Economy 105*(2), 385–411.

Moen, E. R., P. T. Nenov, and F. Sniekers (2021). Buying first or selling first in housing markets. *Journal of the European Economic Association 19*(1), 38–81.

Northcraft, G. B. and M. A. Neale (1987). Experts, amateurs, and real estate: An anchoring-and- adjustment perspective on property pricing decisions. *Organizational behavior and human processes 39*(1), 213–237.

Piazzesi, M., M. Schneider, and J. Stroebel (2020). Segmented housing search. *American Economic Review 110*(3), 720–59.

Pope, J. C. (2008). Buyer information and the hedonic: The impact of a seller disclosure on the implicit price for airport noise. *Journal of Urban Economics 63*(2), 498–516.

Repetto, L. and A. Solis (2020). The price of inattention: Evidence from the swedish housing market. *Journal of the European Economic Association 18*(6), 3261–3304.

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy 82*(1), 34–55.

Rutherford, R. C., T. Springer, and A. Yavas (2005). Conflicts between principals and agents: evidence from residential brokerage. *Journal of Financial Economics 76*(3), 627–665.

Simonsohn, U. and D. Ariely (2008). When rational sellers face nonrational buyers: evidence from herding on ebay. *Management Science 54*(9), 1624–1637.

Taylor, C. R. (1999). Time-on-market as a signal of quality. *Review of Economic Studies 66*(3), 555–578.

Tversky, A. and D. Kahneman (1974). Judgement under uncertainty: heuristics and biases. *Science 185*(4157), 1124–1131.

von Graevenitz, K. and T. E. Panduro (2015). An alternative to the standard econometric approaches in hedonic house price models. *Land Economics 91*(2), 386–409.

*For online publication*

# A Detailed institutional background

## The process of buying and selling

### Realtors

Most sales of houses and apartments in Norway are brokered by a realtor, who is hired by the seller. In contrast to the practice in some other countries, the buyer does not hire a separate realtor. Norwegian law imposes a responsibility on the realtor to protect the interests of both the seller and the buyer, and the realtor is obliged to advise both the seller and the buyer on issues that may impact the selling process.

There exist 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 custom that sellers hire realtors. 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.[36] After 2016, we do not have appraisal values.

The process encompassed a physical visit of the appraiser and the appraiser would inspect prior to the unit's 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,

[36] 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'.

an appraiser would identify the need for drainage, water pressure checks, and potential moisture problems.[37] When a unit was listed for sale, the appraisal value and the technical report were known to prospective buyers.[38] 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 became 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 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. Moreover, given that other realtors use the sell-ask spread, it is most likely not in a realtors self-interest to use the sell-appraisal spread since it often is somewhat smaller and clients cannot compare it across realtors. Thus, the practice of using the sell-ask spread may be a Nash equilibrium.

The econometricians, however, can use the sell-appraisal spread as a perfor-

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

[38]Appraisers are still typically hired to write a report, but the realtor is responsible for estimating the market value of a unit. Today, realtors are assisted be digital tools delivered the the analytics firm, Eiendomsverdi, and automatic valutation methods (AVM) are employed.

mance measure, even if it is not easily available to the sellers.

**The selling process**

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 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 (the 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 and would seek legal sanctions against realtors that are associated with multiple sales in which bids above the ask price are declined.

A seller is not obliged to accept a bid at, or even above, the ask price. For instance, sellers may update their beliefs about the market value of the unit conditional on number of viewers at the open house, or general market developments, which will lead them to reject offers at or above the initial ask price. Sellers may even justify turning down a bid due to a sudden change of heart. The sellers are 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 she does not want to be associated with unlawful ask prices. The realtor is aware that her 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 she can choose an ask price. The legislation consequently incentivizes the realtor to avoid being associated with unlawful ask prices.

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

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

### The buying process

Buyers first consult their bank in order to obtain proof of financing. Prospective buyers document their own and their household's income, debts and assets, as well as civil status. The bank assesses the financial ability of the applicant.[40] 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.

Proof of financing is typically valid for three months. During this period, the buyer visits units of interest within the budget. Having found a unit of interest, the buyer places her bid. Since all bids are legally binding, most buyers only bid in one auction at the time.[41]

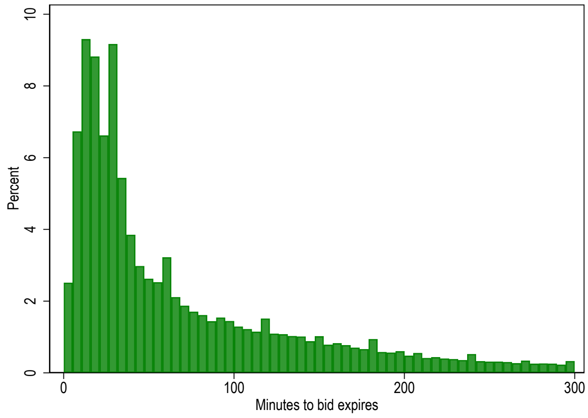
### The auction

The sale of a unit takes place through an ascending-bid auction. Bids are placed 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 bidders make the first bid, they typically submit proof of financing, although this practice is cloaked in some technicalities since buyers do not want to inform the realtor of their 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 A.2 and Figure A.3.

[40] 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.

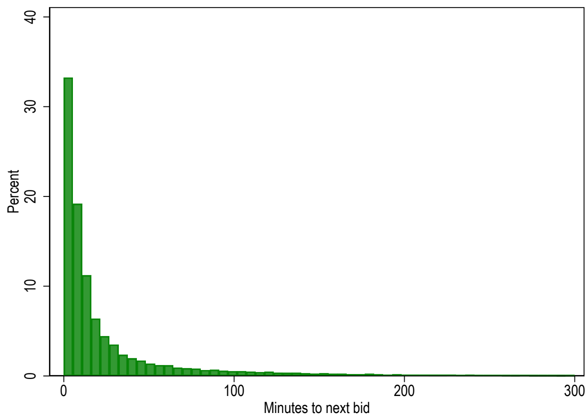
[41] It is legal, and common, to place conditions on bids. The conditions usually involve an expiration time, e.g. 30 minutes or noon the next day, but conditions may also include obtaining a statement about access to financing.

**Figure A.1: 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 A.2: Histogram of minutes to a new bid is placed. Norway, 2007-2015**

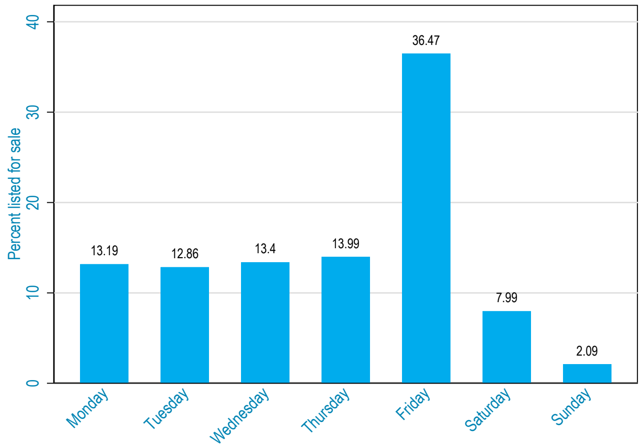



**Notes:** The figure shows a histogram of minutes to a new bid is placed for all bids recorded in auctions with at least two bidders. The of minutes to a new bid is placed is truncated at 6 hours to get a better visual impression of the distribution.

## Descriptive figures and tables

### Day of advertising

**Figure A.3: 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.

### Sell price, opening bid, and number of bidders

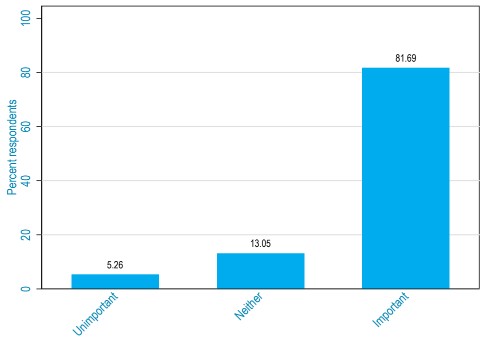
**Table A.1: Sell-appraisal spread on number of bidders and opening bid-appraisal spread. Units sold at least twice. Norway, 2007–2015**

| | Outcome variable: Sell-appraisal spread | | |
|---|---|---|---|
| | (I) | (II) | (III) |
| No. bidders | 2.000*** | | 2.648*** |
| | (0.085) | | (0.082) |
| Op. bid-App. spr. | | 0.376*** | 0.525*** |
| | | (0.022) | (0.018) |
| No. obs. | 5,121 | 5,121 | 5,121 |
| Adj. $R^2$ | 0.484 | 0.457 | 0.658 |
| *Controls:* | | | |
| Common debt | ✓ | ✓ | ✓ |
| Appraisal | ✓ | ✓ | ✓ |
| Realtor FE | ✓ | ✓ | ✓ |
| Realtor office FE | ✓ | ✓ | ✓ |
| Year-by-month FE | ✓ | ✓ | ✓ |
| Unit FE | ✓ | ✓ | ✓ |

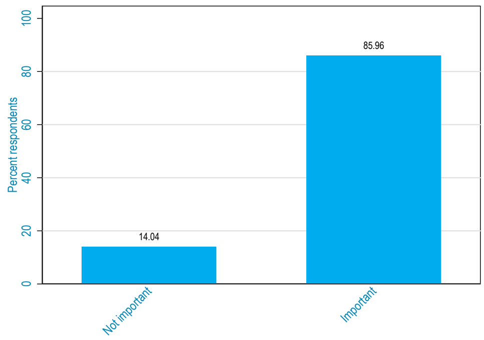
**Notes:** The table shows results from regressing the sell-appraisal spread on number of bidders and the distance between the opening bid and the appraisal value. The first two columns show results when only one of the variables are included, whereas the final column shows results when both variables 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. Standard errors are clustered at the zip-code level. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

# B Survey results

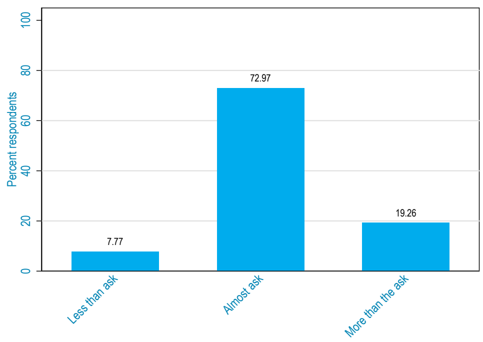
**Figure B.1: Survey results, continues on next page**



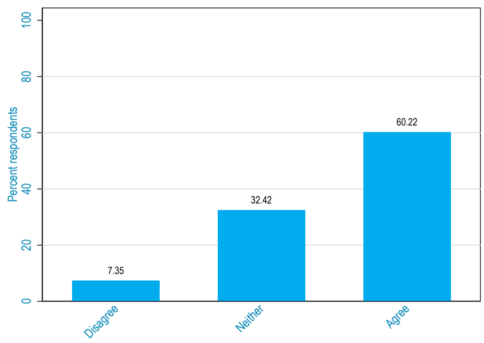

(a) How important is the realtor in deciding the ask price?




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



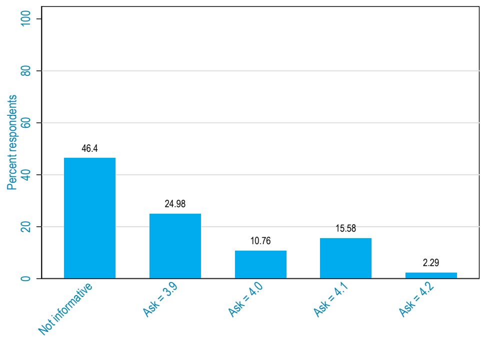

(c) What do you expect regarding the purchase price when you buy?



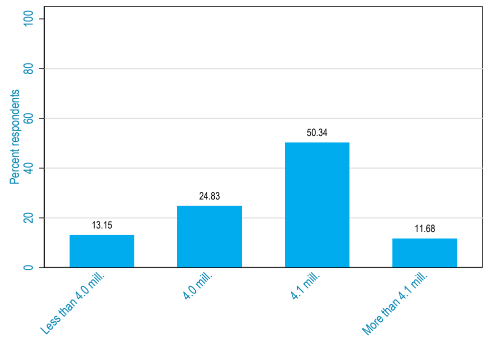

(d) Do you think a lower ask price attracts more bidders?

**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 B.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.

# C Additional results

## Additional data used in the paper

**Table C.1: Share unsold, 2012-2015**

| Year | No. Unsold | No. Sold | Share unsold |
|---|---|---|---|
| 2012 | 733 | 17,663 | 0.04 |
| 2013 | 1,119 | 18,285 | 0.06 |
| 2014 | 623 | 16,945 | 0.04 |
| 2015 | 511 | 18,728 | 0.03 |

**Notes:**: Sold is short notation for transaction data from Eiendomsverdi. Unsold is short notation for data from Eiendomsverdi on units put up for sale on the online platform Finn.no, but not sold within 365 days. Frequencies computed before trimming. The frequencies of no. sold refers include observations without appraisal value.

**Table C.2: Summary statistics for transaction-level data for all real estate companies. Segmentation on ask price-appraisal value differential. Norway, 2007–2015**

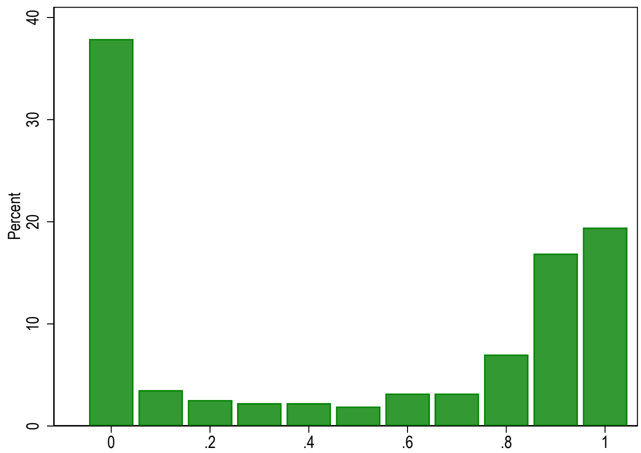
| | Ask price < Appraisal value | | Ask price $\geq$ Appraisal value | |
|---|---|---|---|---|
| Variable | Mean | Std. | Mean | Std. |
| Sell (in 1,000 USD) | 428.40 | 214.30 | 416.71 | 229.60 |
| Ask (in 1,000 USD) | 415.66 | 210.83 | 405.97 | 222.64 |
| Appraisal (in 1,000 USD) | 430.75 | 218.10 | 404.94 | 222.63 |
| Square footage | 1011.69 | 513.81 | 1093.06 | 521.70 |
| Mark-down (in %) | 3.57 | 3.91 | -0.35 | 3.89 |
| Sell-App. spr. (in %) | -0.14 | 9.54 | 3.11 | 9.42 |
| Sell-Ask spr. (in %) | 3.52 | 8.74 | 2.76 | 8.82 |
| Perc. owner-occupied | 63.13 | | 67.30 | |
| 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 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.

## Exogeneity of the appraisal value

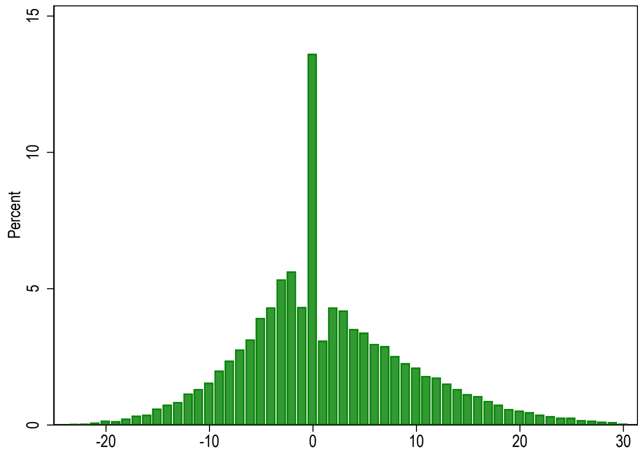
### Common practice

**Figure C.1: Fraction of units sold with appraisal value across Norwegian municipalities.**



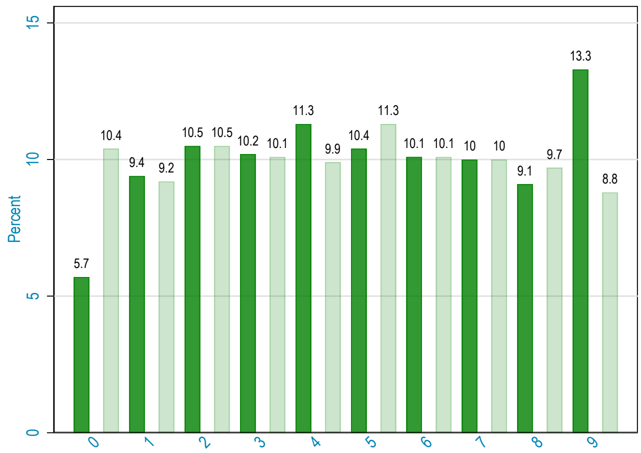

**Notes:** The first axis in the figure denotes the municipality-level share of transactions with appraisal value. The second axis is the percentages of municipalities across Norway with the given share. Thus, 0 on the first axis represents municipalities in which the share of transactions with appraisal values is zero or close to zero. We observe that almost 40 percent of municipalities had this low frequency. Conversely, 1 on the first axis represents a municipality-level share of transactions with appraisal value close to or equal to one hundred percent. We observe that almost 20 percent of municipalities are such that all or almost all transactions have appraisal values. Around fifty percent of municipalities have shares of 0.7 or above.

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



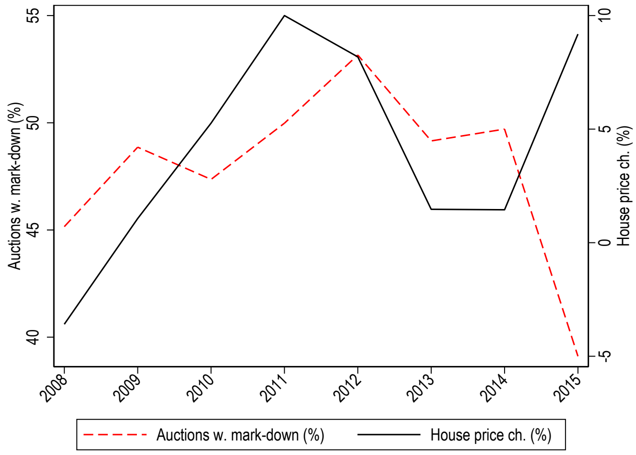

**Notes:** The figure shows a histogram of the sell-appraisal spread for all transactions recorded in the auction level data. The sell-appraisal spread is truncated at -20% and 20% to get a better visual impression of the distribution.

**Figure C.3: Distribution of second digit (NOK 100 ths.) of ask price and appraisal value**




**Notes:** The histogram shows the distribution of the second digit (100 ths. NOK) of the ask price (dark green) and the appraisal value (light green). 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 C.4: Percent units advertised with mark-down versus median house price change in percent. Norway, 2007–2015**

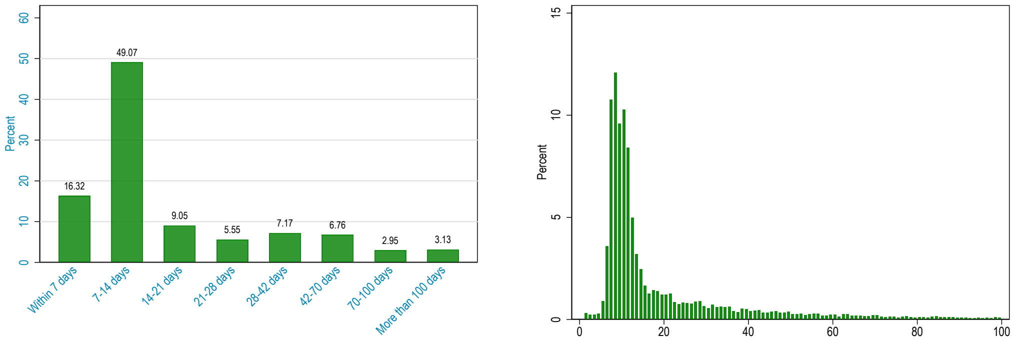



**Notes:** The figure shows the percentage number of transactions in which a mark-down (ask price lower than appraisal value) is used over time (left y-axis) and median house price growth (right y-axis) in Norway during the same period.

## Possible explanations for a mark-down strategy

### TOM and sales probability

**Figure C.5: Distribution of time-on-market**




(a) TOM distribution

(b) Histogram for TOM less than 100 days

**Notes:** The figure shows the TOM-distribution in Norway. TOM is measured as the number of days elapsed between the initial listing and the sales date. In Panel a), we show the full TOM-distribution when we split TOM into different categories. In Panel a), we show the TOM-distribution without any categories, but for TOM less than 100 days.

**Table C.3: Size of mark-down and realtor skills**

| Outcome variable: Mark-down | | |
|---|---|---|
| | (I) | (II) |
| Constant | 2.152*** | 2.124*** |
| | (0.028) | (0.029) |
| Low score | -0.410*** | -0.408*** |
| | (0.037) | (0.038) |
| Normal score | -0.729*** | -0.677*** |
| | (0.036) | (0.037) |
| High score | -0.866*** | -0.818*** |
| | (0.037) | (0.039) |
| Very high score | -1.086*** | -1.061*** |
| | (0.038) | (0.042) |
| No. obs. | 67,276 | 67,272 |
| Adj. $R^2$ | 0.015 | 0.068 |
| *Controls:* | | |
| Realtor office FE | ✗ | ✓ |
| Year-by-month FE | ✗ | ✓ |
| Municipality FE | ✗ | ✓ |

**Notes:** The table shows how the size of the mark-down is related to a realtor performance score. If a realtor belongs to the first quintile in terms of the mean sell-appraisal spread, we characterize this realtor as having a "Very low performance score". If the realtor belongs to the highest quintile in terms of the sell-appraisal spread, he is characterized as having a "Very high performance score". The first column show results without controls. In the second column, we control for realtor-office FE, year-by-month FE, and municipality FE. Standard errors are clustered at the zip-code level. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

## Robustness and sensitivity checks

### Renovation

**Table C.4: Renovation propensity in years around sale. Units with mark-down versus units without 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 |
| $\mathbb{1}\,(Ask < Appraisal)$ | -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 mark-down, and 0 otherwise. This regression amounts to testing whether units with a 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.

### Expiration bids

**Table C.5: Expiration bids and 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 |
| Mark-down | 0.052*** | 0.056*** | 0.066*** | 0.075*** |
| | (0.016) | (0.017) | (0.018) | (0.018) |
| No. obs. | 2471 | 2004 | 1825 | 1727 |
| Pseudo $R^2$ | 0.0760 | 0.0532 | 0.0519 | 0.0545 |
| *Controls:* | | | | |
| Common debt | ✓ | ✓ | ✓ | ✓ |
| Appraisal | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Unit FE | ✓ | ✓ | ✓ | ✓ |

**Notes:** The table shows the association between a mark-down and 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 C.6: Mark-down coefficient for selected outcome variables. An instrumental variable approach. Units sold at least twice. Norway, 2007–2015**

| | *Outcome variable:* | | | | |
|---|---|---|---|---|---|
| | No. Interested | No. bidders | Op. bid | Sell-App. | Sell-Ask. |
| Mark-down | 0.249* | 0.051 | -0.956*** | -0.966*** | 0.066 |
| | (0.141) | (0.039) | (0.162) | (0.168) | (0.171) |
| No. obs. | 5,121 | 5,121 | 5,121 | 5,121 | 5,121 |
| Adj. $R^2$ | -0.157 | -0.127 | -0.005 | 0.029 | -0.123 |
| *Controls:* | | | | | |
| Common debt | ✓ | ✓ | ✓ | ✓ | ✓ |
| Appraisal | ✓ | ✓ | ✓ | ✓ | ✓ |
| Realtor FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Realtor office FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year-by-month FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Unit FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| *First stage results:* | | | | | |
| | Parsimonious | Fully specified | | | |
| Frac. mark-down in zip-code | 3.561*** | 2.964*** | | | |
| | (0.107) | (0.210) | | | |
| Adj. $R^2$ | 0.170 | 0.308 | | | |

**Notes:** The table shows how different auction outcomes are affected by increasing the 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 mark-down is only regressed onto the instrument, while the term "Fully specified" refers the first-stage regression in a 2SLS. Standard errors are clustered at the zip-code level. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

### Compositional bias

**Table C.7: 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. interested | No. bidders | Op.bid-App. spr. | Sell-App. spr. | Sell-Ask. spr. |
| Baseline | 5121 | 0.117*** | 0.038*** | -0.908*** | -0.804*** | 0.224*** |
| | | (0.037) | (0.011) | (0.052) | (0.052) | (0.054) |
| Norway ex. Oslo | 3519 | 0.129*** | 0.031** | -0.905*** | -0.801*** | 0.218*** |
| | | (0.040) | (0.012) | (0.060) | (0.061) | (0.063) |
| Houses | 846 | 0.225** | 0.068*** | -0.991*** | -0.642*** | 0.386*** |
| | | (0.089) | (0.019) | (0.138) | (0.125) | (0.128) |
| Owner occ. | 2735 | 0.163*** | 0.047*** | -0.861*** | -0.760*** | 0.260*** |
| | | (0.051) | (0.015) | (0.074) | (0.070) | (0.072) |
| App. $\leq$ med(App.) | 3055 | 0.066 | 0.025 | -0.862*** | -0.777*** | 0.257*** |
| | | (0.054) | (0.017) | (0.073) | (0.079) | (0.082) |
| App. $>$ med(App.) | 1219 | 0.119 | 0.044** | -0.937*** | -0.818*** | 0.201* |
| | | (0.088) | (0.019) | (0.103) | (0.111) | (0.114) |
| Size $\leq$ med(Size) | 3494 | 0.121** | 0.032** | -0.920*** | -0.846*** | 0.182*** |
| | | (0.053) | (0.016) | (0.066) | (0.067) | (0.069) |
| Size $>$ med(Size) | 1094 | 0.010 | 0.015 | -0.919*** | -0.923*** | 0.106 |
| | | (0.080) | (0.017) | (0.125) | (0.111) | (0.114) |
| TOM $\leq$ med(TOM) | 1176 | 0.249* | 0.045 | -1.231*** | -0.728*** | 0.323* |
| | | (0.131) | (0.041) | (0.156) | (0.165) | (0.168) |
| TOM $>$ med(TOM) | 859 | 0.200 | 0.040 | -1.092*** | -0.665*** | 0.353** |
| | | (0.126) | (0.026) | (0.163) | (0.152) | (0.156) |

**Notes:** The table shows the impact on different auction outcomes by increasing the 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. Standard errors are clustered at the zip-code level. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

**Results from estimated hedonic model**

**Table C.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 | 2.802*** |
| | (0.704) |
| Log(size) | -1370.993*** |
| | (44.217) |
| $(Log(size))^2$ | 112.374*** |
| | (3.030) |
| Log(size)× Apartment | 71.617 |
| | (56.542) |
| $(Log(size))^2\times$ Apartment | 3.814 |
| | (4.058) |
| Log(size)× Oslo | -213.356*** |
| | (9.927) |
| $(Log(size))^2\times$ Oslo | 28.841*** |
| | (0.783) |
| No. obs. | 111,330 |
| Adj. $R^2$ | 0.806 |
| *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 C.9. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

**Table C.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. interested | No. bidders | Op.bid-Pred. spr. | Sell-Pred. spr. | Sell-Ask spr. |
|---|---|---|---|---|---|
| Hedonic mark-down | 0.075*** | 0.029*** | -0.919*** | -0.850*** | 0.158*** |
| | (0.015) | (0.003) | (0.017) | (0.018) | (0.017) |
| No. obs. | 7,034 | 7,034 | 7,034 | 7,034 | 7,034 |
| Adj. $R^2$ | 0.439 | 0.235 | 0.928 | 0.940 | 0.322 |
| *Controls:* | | | | | |
| Common debt | ✓ | ✓ | ✓ | ✓ | ✓ |
| Appraisal | ✓ | ✓ | ✓ | ✓ | ✓ |
| Realtor FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Realtor office FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year-by-month FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Unit FE | ✓ | ✓ | ✓ | ✓ | ✓ |

**Notes:** The table shows the association between different auction outcomes and the hedonic mark-down (lowering the ask relative to the predicted price obtained from the hedonic regression model reported in Table C.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. Standard errors are clustered at the zip-code level. *** 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 C.10: Mark-down and spreads. Transaction-level data for all real estate companies. Norway, 2007–2015**

| | Sell-App. spr. | Sell-Ask. spr. |
|---|---|---|
| Mark-down | -0.670*** | 0.226*** |
| | (0.084) | (0.023) |
| No. obs. | 174,834 | 174,834 |
| Adj. $R^2$ | 0.336 | 0.240 |
| *Controls:* | | |
| Common debt | ✓ | ✓ |
| Appraisal | ✓ | ✓ |
| | ✓ | ✓ |
| Unit FE | ✓ | ✓ |

**Notes:** The table shows how different auction outcomes are affected by increasing the 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. Standard errors are clustered at the zip-code level. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

**Left-digit bias**

The specification used by Repetto and Solis (2020) 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 $ask_i$, $\beta_j$ 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. 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.

We estimate one specification without controls and one with controls.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.

**Table C.11: 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 | -1.907*** | -1.999*** | -1.199 | -0.431 |
| | (0.514) | (0.542) | (0.756) | (0.802) |
| No. obs. | 22,926 | 21,367 | 14,566 | 13,854 |
| Adj. $R^2$ | 0.977 | 0.981 | 0.025 | 0.206 |
| *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 $ask_i$, $\beta_j$ 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 C.12: 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 | -4.192*** | -4.486*** | -2.350 | -3.649** |
| | (1.446) | (1.493) | (1.727) | (1.780) |
| No. obs. | 4,082 | 3,891 | 3,909 | 3,733 |
| Adj. $R^2$ | 0.973 | 0.979 | 0.038 | 0.279 |
| *Controls:* | | | | |
| Hedonic attributes | ✗ | ✓ | ✗ | ✓ |
| Common debt | ✗ | ✓ | ✗ | ✓ |
| Realtor FE | ✗ | ✓ | ✗ | ✓ |
| Realtor office FE | ✗ | ✓ | ✗ | ✓ |
| Year-by-month FE | ✗ | ✓ | ✗ | ✓ |
| Zip-code FE | ✗ | ✓ | ✗ | ✓ |

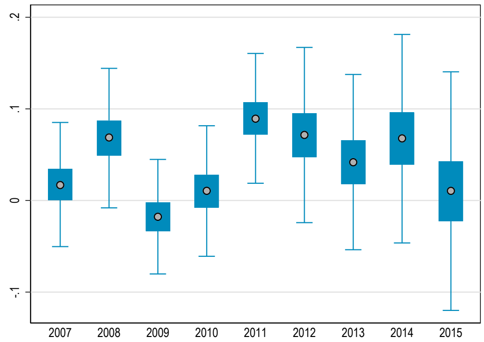
**Notes:** The table report results from estimating a similar specification as in Repetto and Solis (2020). Their specification takes the following form:

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

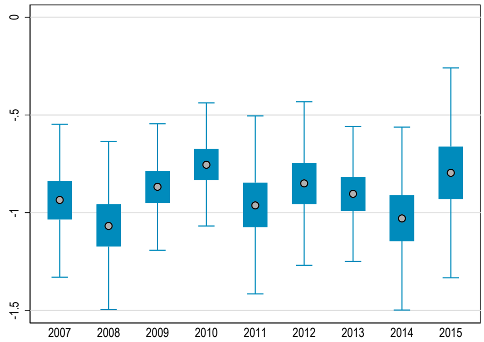
in which $c_j$ is the (logarithm of the) relevant round-million threshold for $ask_i$, $\beta_j$ are threshold-specific intercepts, and $\boldsymbol{X}_i$ are a set of controls. Following Repetto and Solis (2020), we estimate this specification for all ask prices in the interval NOK 100,000 below to 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.

**Variations over the housing cycle. Norway, 2007–2015**

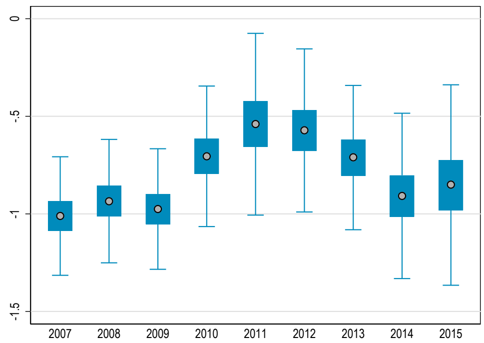
**Figure C.6: Time-variation in the effect of the mark-down on auction variables.**



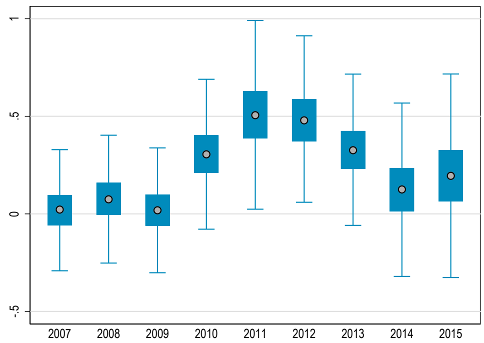

(a) No. bidders




(b) Op. bid-App. spr.




(c) Sell-App. spr.

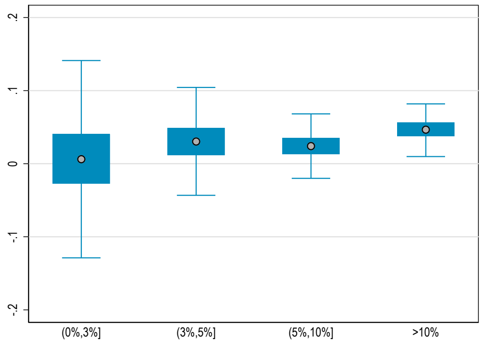



(d) Sell-Ask spr.

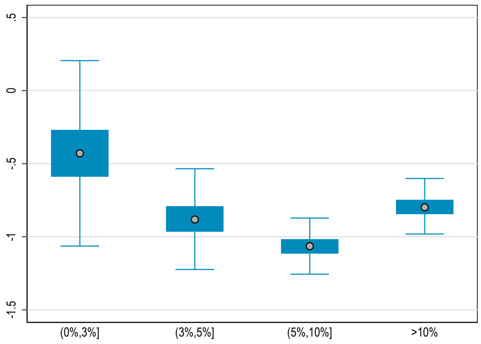
**Notes:** The figure shows year-specific effects of a mark-down on different auction variables. Results are obtained by estimating the baseline regression models in eq. 6 year-by-year. Standard errors are clustered at the zip-code level.

## Non-linearities

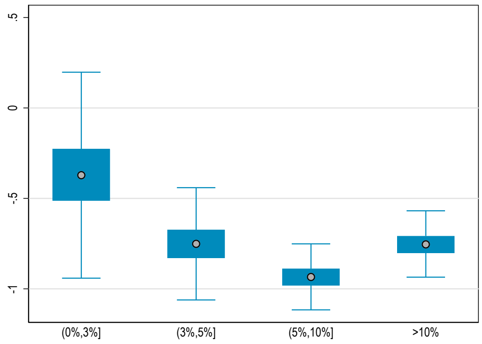
**Figure C.7: Non-linear effects of mark-down on auction variables. Norway, 2007–2015**



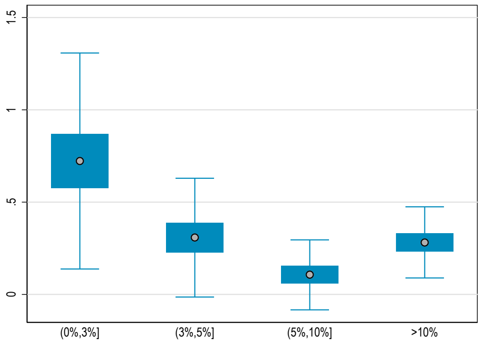

(a) No. bidders




(b) Op. bid-App. spr.




(c) Sell-App. spr.




(d) Sell-Ask spr.

**Notes:** The figure shows effects of a 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. Standard errors are clustered at the zip-code level.

### Mark-up versus mark-down

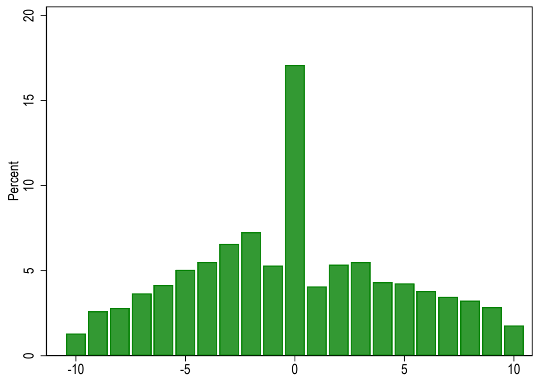
**Table C.13: Mark-down versus mark-up coefficients using unit fixed effects. Units sold at least twice. Norway, 2007–2015**

| | *Dep. var: Sell-App. spread* | |
|---|---|---|
| | (I) | (II) |
| Mark-down | -0.804*** | -0.832*** |
| | (0.052) | (0.052) |
| Mark-up | | 0.827** |
| | | (0.392) |
| No. obs. | 5,121 | 5,121 |
| Adj. $R^2$ | 0.430 | 0.431 |
| *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 mark-down is increased (lowering the ask price relative to the appraisal value) and when the 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. Standard errors are clustered at the zip-code level. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

### Trimming on large sell-appraisal spreads

**Figure C.8: Sell-appraisal spread within the -10 to 10 percent interval**




**Note:** The figure shows the distrubution of the sell-appraisal spread when we zoom in on the interval [-10%,10%].

**Table C.14: Mark-down coefficient for selected outcome variables using unit fixed effects. Units sold at least twice. Norway, 2007–2015. Sell-appraisal spread in the [-10,10] interval.**

| | *Outcome variable:* | | | | |
|---|---|---|---|---|---|
| | No. Interested | No. bidders | Op.bid-App. spr. | Sell-App. spr. | Sell-Ask. spr. |
| Mark-down | 0.137*** | 0.051*** | -0.833*** | -0.569*** | 0.473*** |
| | (0.050) | (0.013) | (0.069) | (0.054) | (0.056) |
| No. obs. | 3,210 | 3,210 | 3,210 | 3,210 | 3,210 |
| Adj. $R^2$ | 0.414 | 0.196 | 0.172 | 0.311 | 0.273 |
| *Controls:* | | | | | |
| Common debt | ✓ | ✓ | ✓ | ✓ | ✓ |
| Appraisal | ✓ | ✓ | ✓ | ✓ | ✓ |
| Realtor FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Realtor office FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year-by-month FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Unit FE | ✓ | ✓ | ✓ | ✓ | ✓ |

**Notes:** The table shows how different auction outcomes are associated with increased mark-down (lowering the ask price relative to the appraisal value), when we trim away spreads falling outside the [-10,10] interval. 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. Standard errors are clustered at the zip-code level. $^{***}$ indicates significance at the 1% level, $^{**}$ indicates significance at the 5% level, $^{*}$ indicates significance at the 10% level.

# D Theory

## Deriving Prediction 3 form Section 3

The sell-ask spread in the micro-founded model is

$$\begin{aligned}\frac{P-a}{a} &= \frac{P}{a}-1=\Pr\{B=1|B>0,\theta\}+\Pr\{B>1|B>0,\theta\}\frac{u}{a}-1\\ &=(1-\Pr\{B>1|B>0,\theta\})+\Pr\{B>1|B>0,\theta\}\frac{u}{a}-1\\ &=\Pr\{B>1|B>0,\theta\}\left(\frac{u}{a}-1\right).\end{aligned}$$

Notice that the first term is increasing in $\theta$, so combining with Eq. (2), it follows that the first term is decreasing in $a$. Similarly, the second term is clearly decreasing in $a$ given $u>a$. It follows that the sell-ask spread is decreasing in $a$.

## Proof of Proposition 1

Let $a(\eta)$ denote the optimal ask price given $\eta$. We first characterize $a(\eta)$ for the extreme values of $\eta=0$ (Realtor has all the bargaining power) and $\eta=1$ (Seller has all the bargaining power) and show that $a(1)>a(0)$.

First, using the properties of the Poisson distribution, we have that the seller and realtor profits can be expressed as

$$V_S(a,\theta)=\exp\{-\mu(\theta)\}z_S+(1-\exp\{-\mu(\theta)\})(1-f)P(a,\theta),$$

and

$$V_R(a,\theta)=\exp\{-\mu(\theta)\}z_R+(1-\exp\{-\mu(\theta)\})fP(a,\theta),$$

respectively.

Using the implicit function $\theta(a)$ linking tightness and ask price via the buyer's directed search (Eq. (1)), we can write the seller's payoff equivalently as

$$\exp\{-\mu(\theta(a))\}z_S+(1-\exp\{-\mu(\theta)\})(1-f)P(a,\theta(a)),$$

and similarly for the realtor.

Next, we re-write the seller and realtor's payoff functions as

$$V_S(a)=(1-f)\left[\exp\{-\mu(\theta(a))\}\chi_S+(1-\exp\{-\mu(\theta(a))\})P(a,\theta(a))\right],$$

and

$$V_R(a)=f\left[\exp\{-\mu(\theta(a))\}\chi_R+(1-\exp\{-\mu(\theta(a))\})P(a,\theta(a))\right],$$

where $\chi_S = \frac{z_S}{1-f}$ and $\chi_R = \frac{z_R}{f}$. Suppose that $\eta = 1$ or $\eta = 0$. In those two cases the seller and realtor maximize $V_S(a)$ and $V_R(a)$, respectively. In either case, the first-order condition for the seller/realtor optimization can be written as

$$-\frac{\partial \mu}{\partial \theta}\frac{d\theta}{da}\exp\{-\mu\}(P-\chi_i) = (1-\exp(-\mu))\left[\frac{\partial P}{\partial a}+\frac{\partial P}{\partial \theta}\frac{\partial \theta}{\partial a}\right], \quad i \in \{S,R\}, \tag{D.1}$$

The left-hand side reflects the marginal effect on the payoff from changing the probability of sale, while the right-hand side reflects the marginal effect of changing the expected sale price.

Let $a_R = a(1)$ and $a_S = a(0)$ denote the optimal ask price for the seller and realtor, respectively and let $\theta_S$ and $\theta_R$ be the corresponding tightness levels.[42] Therefore, if we compute the first-order condition of the realtor at the seller's optimal choice of $a$ (and $\theta$), we get

$$\begin{aligned}
&\frac{\partial \mu(\theta_S)}{\partial \theta}\frac{d\theta(a_S)}{da}\exp\{-\mu(\theta_S)\}(P(a_S,\theta_S)-\chi_R)+\\
&+(1-\exp(-\mu(\theta_S)))\left[\frac{\partial P(a_S,\theta_S)}{\partial a}+\frac{\partial P(a_S,\theta_S)}{\partial \theta}\frac{\partial \theta(a_S)}{\partial a}\right]=\\
&\frac{\partial \mu(\theta_S)}{\partial \theta}\frac{d\theta(a_S)}{da}\exp\{-\mu(\theta_S)\}(P(a_S,\theta_S)-\chi_R)-\\
&-\frac{\partial \mu(\theta_S)}{\partial \theta}\frac{d\theta(a_S)}{da}\exp\{-\mu(\theta_S)\}(P(a_S,\theta_S)-\chi_S)=\\
&\frac{\partial \mu(\theta_S)}{\partial \theta}\frac{d\theta(a_S)}{da}\exp\{-\mu(\theta_S)\}\{\chi_S-\chi_R\}<0,
\end{aligned}$$

where the second line follows by the seller's FOC at the optimum.

It follows that at the seller's optimal ask price choice, the realtor is worse off and, moreover, a marginal decrease in the ask price will increase his payoff. Given a unique ask price choice, it then follows that $a_R < a_S$ and $\theta_R > \theta_S$.

Next we characterize $a(\eta)$ more generally. Using the implicit function $\theta(a)$ given by Eq. (1), and the expressions for the seller and realtor payoffs, we can write Eq. (3) as

$$\begin{aligned}
\max_a &\{(1-f)[\exp\{-\mu(\theta(a))\}\chi_S+(1-\exp\{-\mu(\theta(a))\})P(a,\theta(a))-\chi_S]\}^\eta\\
&\{f[\exp\{-\mu(\theta(a))\}\chi_R+(1-\exp\{-\mu(\theta(a))\})P(a,\theta(a))-\chi_R]\}^{1-\eta}.
\end{aligned}$$

Simplifying, we get

$$\max_a\left\{(1-f)^\eta f^{1-\eta}(1-\exp\{-\mu(\theta(a))\})(P(a,\theta(a))-\chi_S)^\eta(P(a,\theta(a))-\chi_R)^{1-\eta}\right\}.$$

[42]We assume that these values are unique as in our micro-founded example.

Furthermore, taking logs (which is a monotone transformation and thus does not impact the optimization), we get

$$\max_a \{\eta \log(1-f) + (1-\eta)\log f + \log(1-\exp\{-\mu(\theta(a))\})$$
$$+\eta \log(1-f) + (1-\eta)\log f + \log(1-\exp\{-\mu(\theta(a))\})\}$$

Therefore, the first-order condition can be written as

$$-\frac{\exp\{-\mu\}}{1-\exp\{-\mu\}}\frac{\partial \mu}{\partial \theta}\frac{d\theta}{da} = \left(\eta \frac{1}{P-\chi_S} + (1-\eta)\frac{1}{P-\chi_R}\right)\left[\frac{\partial P}{\partial a} + \frac{\partial P}{\partial \theta}\frac{\partial \theta}{\partial a}\right]. \quad \text{(D.2)}$$

Notice that at $\eta = 1$, we recover the f.o.c. from Eq. (D.1) and, similarly for $\eta = 0$.

Given a unique $a$, by the Theorem of the Maximum, $a(\eta)$ is a continuous function. Moreover, we know that $a(1) > a(0)$. Therefore, if we can show that $a(\eta)$ is monotone we can conclude that $a(\eta)$ is increasing in $\eta$. Suppose, toward a contradiction that $a(\eta)$ is not monotone. Therefore, there are two values $\eta_1$ and $\eta_2$, $\eta_1 \neq \eta_2$, such that $a(\eta_1) = a(\eta_2)$. Moreover, these two values of $a$ satisfy Eq. (D.2). Noting that the left-hand side of that equation does not depend on $\eta$ and that the term in square brackets on the right-hand side also does not depend on $\eta$. Moreover $\frac{1}{P-\chi_S}$ and $\frac{1}{P-\chi_R}$ also do not depend on $\eta$. Therefore, using these observations we arrive at the equality

$$\eta_1 \frac{1}{P-\chi_S} + (1-\eta_1)\frac{1}{P-\chi_R} = \eta_2 \frac{1}{P-\chi_S} + (1-\eta_2)\frac{1}{P-\chi_R},$$

or equivalently

$$(\eta_1 - \eta_2)\left(\frac{1}{P-\chi_S} - \frac{1}{P-\chi_R}\right) = 0.$$

However, for $\chi_S \neq \chi_R$ this can only be true iff $\eta_1 = \eta_2$, which is a contradiction with our assumption that there are two different values of $\eta$ that give the same value of $a$. Therefore, $a(\eta)$ is monotone. Since $a(1) > a(0)$, it follows that $a$ is increasing in $\eta$. $\square$

## Sale probability-ask price gradient

Using the micro-founded Stage 0 utility of the buyer, we can derive the implicit relationship $\theta(a)$ as

$$\overline{U} = U(a,\theta) = \Pr\{B=1|\theta\}(u-a).$$

Therefore by the implicit function theorem,

$$\frac{d\theta}{da} = \frac{\Pr\{B=1|\theta\}}{\partial \Pr\{B=1|\theta\}/\partial\theta}\frac{1}{u-a}.$$

The probability of sale is $s = \Pr\{B > 0|\theta\}$, so that

$$\frac{\partial s}{\partial a} = \frac{\partial \Pr\{B > 0|\theta\}}{\partial \theta}\frac{d\theta}{da} = \frac{\partial \Pr\{B > 0|\theta\}}{\partial \theta}\frac{\Pr\{B = 1|\theta\}}{\partial \Pr\{B = 1|\theta\}/\partial\theta}\frac{1}{u-a}.$$

In a dynamic model, average time-on-market $TOM$ is one over the sale probability. Therefore,

$$\frac{\partial TOM}{\partial a} = -\frac{1}{s^2}\frac{\partial s}{\partial a} = -\frac{1}{\Pr\{B > 0|\theta\}}\frac{\partial \Pr\{B > 0|\theta\}/\partial\theta}{\Pr\{B > 0|\theta\}}\frac{\Pr\{B = 1|\theta\}}{\partial \Pr\{B = 1|\theta\}/\partial\theta}\frac{1}{u-a} > 0.$$

In terms of the magnitude, note that we can further write this as

$$\frac{\partial TOM}{\partial a} = -\frac{1}{\Pr\{B > 0|\theta\}}\frac{\varepsilon_{\Pr\{B>0\},\theta}}{\varepsilon_{\Pr\{B=1\},\theta}}\frac{1}{u-a},$$

where $\varepsilon_{B>0,\theta}$ is the elasticity of $\Pr\{B > 0\}$ with respect to $\theta$ and similarly for $\varepsilon_{\Pr\{B=0\},\theta}$. Therefore,

$$\frac{\partial TOM}{\partial a} = TOM\frac{\varepsilon_{\Pr\{B>0\},\theta}}{\left|\varepsilon_{\Pr\{B=1\},\theta}\right|}\frac{1}{u-a}.$$

This gradient is larger the larger is TOM, the larger is the elasticity of the sale probability with respect to $\theta$, the smaller is the elasticity of negotiated sale with respect to $\theta$ and the smaller is the surplus a buyer gets from a negotiated sale.

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