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Match Quality and House Price Dispersion: Evidence from Norwegian Housing Auctions

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AUTHORS:
ANDRÉ ANUNDSEN
ARNE LYSHOL
PLAMEN T. NENOV
ERLING RØED LARSEN

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Match Quality and House Price Dispersion: Evidence from Norwegian Housing Auctions*

André K. Anundsen
Housing Lab, Oslo Metropolitan University

Arne Lyshol
BI Norwegian Business School

Plamen T. Nenov
Norges Bank
and BI Norwegian Business School

Erling Røed Larsen
Housing Lab, Oslo Metropolitan University
and BI Norwegian Business School

Abstract

Assessing the quantitative relevance of match quality and search frictions for house price dispersion is key to understanding house price formation and the importance of uninsurable housing wealth shocks. In this paper, we use a unique auction-level data set from Norway, combined with a structural model of the housing transaction process that includes frictional arrival and endogenous entry of buyers into bidding, as well as information frictions between buyers and sellers, to determine the importance of buyer taste heterogeneity for house prices and price dispersion. We find that quality differences matter greatly for house price dispersion, well beyond what hedonic pricing models may suggest, while buyer taste heterogeneity accounts for the majority of the remaining price dispersion. Our structural model implies that list prices often deviate substantially from seller valuations, lending support to theories of list price determination that feature strategic interactions between sellers/agents and buyers.

Keywords: structural estimation, search frictions, buyer-specific valuations, bidding wars, list price, selection effects, informational mismatch, overbidding

JEL classification: R21, R31

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1 Introduction

Housing markets are characterized by substantial price dispersion even among properties that share common features, such as location, type, size, and number of rooms. One possible driver of this residual price dispersion is quality differences, which remain unobserved to researchers, but which are observable to owners and potential buyers. Such quality differences are reflected in sale prices. Nevertheless, even when one is able to better account for such quality differences, there is still substantial residual price variation.[1] This residual price variation suggests other possible drivers. One such alternative is the frictional process of searching and matching between properties and buyers with heterogeneous tastes. This is a very natural candidate since transacting housing is characterized by substantial trading delays and informational frictions.

Understanding the importance of frictional matching for house prices and price dispersion goes beyond understanding the workings of housing markets. Since housing wealth tends to comprise a substantial share of household wealth, the nature of house price dispersion may determine whether home owners are exposed to potentially large uninsurable (housing) wealth shocks. Indeed, if frictional matching plays an important role in driving house price dispersion, then a buyer who has been lucky to match well with her current home (and has paid a relatively high price for it) might later end up as the unlucky seller of that same property when she has to either accept a lower price from a buyer that does not value the property as much or continue searching, possibly facing costly delays.

In this paper we use a unique auction-level data set for Norway combined with a structural model of the housing transaction process to determine the contribution of match quality due to buyer preference heterogeneity and frictional matching to house prices and price dispersion. We find that buyer preference heterogeneity can account for a sizable share of the price dispersion that is not accounted for by quality difference. Nevertheless, quality differences play the main role in driving house price dispersion, even well beyond what a typical hedonic pricing model would suggest. Moreover, our structural model implies that there is an important *causal* effect of the number of bidders on house prices and that list prices often deviate substantially from seller valuations.

Our data comprise detailed bidding logs and information on open-house visitors from all sales handled by two of the largest realtor companies in Norway for the period 2010–2015. The data set includes a unique bidder identifier, which allows us to compute the number of bidders associated with each transaction but also to follow the bidding behavior of each unique bidder in the auction. In addition, we have information on the list and sale dates, the list price and sale price, as well as standard hedonics. In Norway, all bids and acceptances of bids are legally binding. This allows us to identify one specific date upon which transfer of ownership is essentially determined.

[1] See Section 6.1 below for details.

Our structural model of the housing transaction process incorporates some features of the Norwegian institutional context, but is also applicable to other countries in which some housing units transact via an auction or auction-like format. The model comprises a frictional buyer entry game into bidding combined with rich dwelling, buyer, and seller heterogeneity. In the model, a number of potential buyers (drawn randomly according to some distribution of open-house visitors) observe the quality of a property as well as their idiosyncratic tastes for it. In addition, they observe a signal of the seller reservation value in the form of the list price. Importantly, we allow for some decoupling between the seller reservation value and the list price in terms of a systematic bias, as well as some dispersion between the reservation value and the list price. Therefore, list prices in our model are possibly biased noisy signals of seller reservation values. This property of the list price incorporates a number of theories of list price formation proposed in the literature.

Upon observing this information about the property and the seller, buyers endogenously choose whether to enter a bidding stage by paying a specific transaction cost or to walk away. Importantly, the transaction cost does not scale with the quality of the property, so that a potential buyer is more likely to enter bidding if the property has higher quality. In addition, buyers are more likely to bid if they have sufficiently high idiosyncratic taste, or when the list price is lower. Since buyer entry decisions are strategic substitutes, a larger number of potential buyers (i.e., open-house visitors) leads to a lower probability of buyer entry, other things equal.

At the bidding stage buyers observe the true seller reservation value. Due to imperfect information at the entry stage, some bidders may actually have a lower valuation than the seller, a situation we call *informational mismatch*. Indeed, it can be the case that there are multiple bidders but the unit does not end up selling. Depending on the number of entering bidders who have a higher valuation than the seller reservation value, the transaction price is either determined in a reduced-form negotiation process in the case of a single bidder or through a second-price auction. These features of the model lead to rich selection effects due to the interaction of quality with buyer and seller heterogeneity, and the underlying frictions, justifying a fully structural estimation.

We estimate our model using Simulated Method of Moments (SMM). Since our data span a large number of different locations, types of housing, and time periods, we define a number of segments based on property type (Small vs. Large apartments vs. Houses) and time period (each year in our sample). Given the need for segmentation and our data coverage, we focus attention on segments in Oslo, the capital city of Norway. For each segment, we construct moments based on an artificial data set of sales. For our estimation, we let the mean and standard deviation of quality vary by segment, while the dispersion in buyer idiosyncratic tastes, the mean and dispersion of seller reservation values, the mean and dispersion of the list price bias, or "wedge", from the seller reservation value, and the transaction cost are time-invariant. All parameters vary by housing type. Identification in our estimation framework requires that each parameter changes the moments used in the estimation in a "unique" way and that the moments are sufficiently responsive to changes in parameters. As an example for how identification works in our framework, we can identify the dispersion in buyer-specific tastes separately from the dispersion in housing quality, since list price dispersion responds to quality dispersion but not to buyer taste dispersion. On the other hand, buyer taste dispersion affects the average sale price and the probability of sale, while quality dispersion does not.

The model matches the targeted moments very well, despite the substantial over-identification in our baseline estimation – there are in total 54 moments against 18 parameters for each housing type. It also performs well against a number of non-targeted moments, including direct measures of buyer and seller valuations. Specifically, we use the detailed bidding information from our data set to construct lower and upper bounds on the valuations of bidders who participate in auctions (i.e., there are at least two bidders) and who do not end up submitting the highest final bid. Similarly, we compute a proxy for the seller reservation value by considering bidding logs in which the seller makes a (legally binding) counter-bid.

We estimate a dispersion parameter for buyer-specific tastes of between 0.032 and 0.047, depending on the type of housing, which corresponds to an interquartile range of between 0.05 and 0.07.[2] We also find a sizable dispersion in seller specific-preferences, as well as substantial dispersion between list prices and seller reservation values. On the other hand, we estimate a small and insignificant mean bias in list prices.

Our estimated model parameters imply a much more important role of quality differences for price dispersion than suggested by hedonic pricing models. Indeed, fully accounting for quality differences in our model implies an R^2 statistic between 97 and 99 percent. In contrast, the typical hedonic regression tends to have an R^2 of around 80 to 90 percent.[3] Therefore, much of the "residual" house price variation from typical hedonic pricing models is likely due to unobservable quality differences. However, we find that most of the remaining variation in prices can be accounted for by match quality, determined by the dispersion in idiosyncratic buyer tastes. Specifically, our estimated model implies that match quality accounts for between 2.5 to 4 percentage points of the observed house price dispersion in Oslo during 2010–2015. Moreover, buyer preference heterogeneity also impacts the observed average price level, contributing to around 5 to 7 percent higher prices in Oslo during 2010–2015. Beyond match quality, the dispersion in seller-specific preferences also affects the observed house price dispersion but the effect is around 1/5 to 1/3 of the effect through buyer taste heterogeneity.

[2] We assume that buyer idiosyncratic tastes follow a Type-I extreme value distribution.

[3] For example, Anundsen and Røed Larsen (2018) show that for Norway a typical hedonic model with observable attributes explains around 85 percent of the price variation in the Norwegian housing market. See Section 6 for additional discussion.

We also show by estimating reduced-form regressions of sale prices on number of bidders using simulated transaction data from our estimated model that there is an important *causal* effect of number of bidders on prices even after fully controlling for quality. Since bidder entry correlates positively with quality in our model, other things equal, not accounting for quality leads to a upward bias in the estimated effects of bidders on prices. Whenever we fully account for quality, we recover a causal effect of one more bidder of slightly less than 0.01 log points or approximately 1 percent. This is close to reduced-form estimates in the literature, which provides one more independent validation of our structural model.

Finally, we consider an extension of our structural model where we allow for buyers engaging in "overbidding" depending on the number of other buyers that enter bidding, a channel that has been suggested in behavioral models of auction dynamics. Estimation of this extended model reveal a marginal overbidding effect of around 1 p.p for every additional bidder that enters bidding. Consequently, overbidding ends up playing an important role for driving residual price dispersion. It also amplifies the role of determinants of list price dispersion such as the seller-specific preferences and the dispersion in the list price wedge for house price dispersion.

While our structural model is particularly suited for the specific institutional features of the Norwegian housing market, our modeling approach and empirical methodology are also applicable more broadly to housing markets where ”bidding wars” and quasi-auctions are not uncommon. For example, Han and Strange (2014b) argue that bidding wars have been an increasingly common phenomenon in the U.S., increasing in frequency during the early 2000, with more than 30 percent of transactions in some local U.S. housing markets characterized as bidding wars. For comparison, 51 percent of the transactions in the Oslo housing market can be characterized as "bidding wars" according to their definition. Recent developments in the U.S. housing market also look more similar to the Norwegian market in that the list price does not represent a binding ceiling on the sale price.

Related Literature

Our paper bridges two large literatures. First, our focus on understanding the contribution of match quality to house price dispersion and the assumption of stochastic arrival of (potential) buyers relate our paper to a growing literature on search frictions in housing markets (Wheaton (1990), Krainer (2001), Novy-Marx (2009), Caplin and Leahy (2011), Genesove and Han (2012), Carrillo (2012), Anenberg and Bayer (2013), Diaz and Jerez (2013), Head et al. (2014), Ngai and Tenreyro (2014), Nenov et al. (2016), Guren (2018), Guren and McQuade (2020), Ngai and Sheedy (2019), Moen et al. (2021), Piazzesi et al. (2020), Grindaker et al. (2021), Kotova and Zhang (2021), Rekkas et al. (2021) among others).[4] Second, our explicit modeling of the transaction process, whether through bargaining or as a second-price auction combined with a costly entry decision by potential buyers brings our paper close to the literature on auctions versus negotiations in housing markets (Ashenfelter and Genesove (1992), Mayer (1995), Lusht (1996), Merlo and Ortalo-Magne (2004), Genesove and Hansen (2014), Han and Strange (2014a), Chow et al. (2015), Genesove and Han (2016), Arefeva (2020), Gargano and Giacoletti (2020), Han et al. (2021)).[5]

Our paper is most closely related to recent work by Genesove and Han (2016) and Rekkas et al. (2021). Genesove and Han (2016) use a semi-structural model and survey data on number of bidders combined with data on sale and list prices and standard hedonics to estimate the dispersion in buyer-specific valuations. The key moment used is the reduced-form coefficient of number of bidders on (log) prices, which in a static auction setting with two or more bidders and independent private values maps into the dispersion in buyer-specific tastes.[6] We differ from and complement this paper in a number of ways. First, we rely on a fully-specified structural model of the transaction process, which can account for a variety of important selection effects on the set of transacted dwellings, due to the interaction of quality differences, seller heterogeneity, and information frictions with the endogenous buyer entry into bidding. Second, our identification of buyer-specific taste dispersion relies on a different set of moments, while we use the reduced-form coefficient of number of bidders on prices to validate our estimated model. This is important for consistently identifying this key parameter, since the reduced-form coefficient of number of bidders on prices appears to be sensitive to fully accounting for quality differences across objects.

In independent and contemporaneous work, Rekkas et al. (2021) study a rich structural housing search model, which they estimate using housing transaction data from Vancouver. Some of the features of their model are qualitatively similar to ours. For example, their model features price posting and directed search, while list prices in our model carry information about seller reservation values, and affect entry into bidding. There are also important differences, however. Most importantly, their model abstracts from the possibility of auctioned sales, or informational mismatch, whereby there is no trade despite entry of bidders. These differences imply that the two models are complementary and can be applied to housing markets with different institutional settings. Consequently, the data used to discipline the two models are also different, with Rekkas et al. (2021) relying on transaction-level data, while we exploit a unique auction-level

[4]See Han and Strange (2015) for a review of this literature.

[5]See also McAfee and McMillan (1987), Levin and Smith (1994), and Bulow and Klemperer (1996, 2009) for theoretical treatments of auctions versus negotiations in the presence of entry costs.

[6]The authors report dispersion estimates for a number of underlying distributions for buyer-specific tastes. For a Type-1 extreme value distribution, they report an interquartile range of around 0.09. Our estimates suggest a lower interquartile range of between 0.05 and 0.07 depending on the type of housing.

data set with full bidding logs. Still, despite these differences, the two papers reach a similar conclusion, namely that quality differences (or property heterogeneity) play the main role in explaining house price dispersion.[7]

Our structural estimation approach brings our paper close to a large literature in structural industrial organization dealing with structural estimation of game-theoretic auctions models (see Paarsch (1992), Laffont et al. (1995), Donald and Paarsch (1996), Elyakime et al. (1997), Guerre et al. (2000), Li et al. (2000), Athey and Haile (2002), Li et al. (2002), Bajari and Hortaçsu (2003), Haile and Tamer (2003), Jofre-Bonet and Pesendorfer (2003), Athey et al. (2011), Krasnokutskaya (2011), Coey et al. (2017), Freyberger and Larsen (2022), Backus and Lewis (2023), among others). While some of the structural details of our model are standard for the auction literature (particularly with respect to the transaction protocol), the informational frictions at the entry stage are an innovation that is necessary given the application of our model to housing auctions. Furthermore, to the best of our knowledge, out paper is the first to structurally estimate an entry game combined with auction model using housing auction data.

Finally, our study is related to a growing literature on list prices in housing markets and their relation to sale prices (Horowitz (1992) Taylor (1999), Genesove and Mayer (2001), Haurin et al. (2013), Merlo et al. (2015), (Han and Strange, 2016), Liu and van der Vlist, 2019, Repetto and Solis (2019), Gargano and Giacoletti (2020), Anundsen et al. (2022b). We contribute to this literature by empirically uncovering a systematic disconnect and positive dispersion in the wedge between seller reservation values and list prices.[8]

The rest of the paper is organized as follows. We start by describing the institutional details of the Norwegian housing market, before proceeding to lay out the structural model in Section 3. Section 4 presents the data and details the estimation approach. Section 5 presents and discusses the estimation results and validates the model against a number of non-targeted moments, while Section 6 presents our counterfactual exercises. Finally, Section 7 discusses an extension of our model, while Section 8 provides brief concluding comments.

[7]For the most part, quantitative models of housing with frictional search, which include buyer taste heterogeneity, tend to abstract from the possibility of auctioned sales (Carrillo (2012), Ngai and Tenreyro (2014), Guren (2018), Ngai and Sheedy (2019), Guren and McQuade (2020)).

[8]In addition, estimating a positive marginal overbidding effect in our extended model also lines up with recent reduced-form findings by Gargano and Giacoletti (2020) that analyzes an underquoting policy reform in Australia.

2 Institutional setting

In this section, we provide a brief overview of the institutional background of the Norwegian housing market.[9] When sellers decide to sell a housing unit in Norway, they typically do so with the help of a realtor. Even though the realtor is hired and paid by the seller, the realtor is required by law to take into account the interest of both the seller and the buyer. The typical realtor commission rate is around 2 percent of the sale price. Unlike other countries, it is very uncommon for buyers to hire a buyer-agent in Norway. The seller decides on a list price with input from the realtor, before listing the unit for sale, typically using the nationwide online service Finn.no and national and local newspapers. In most cases the realtor then organizes one or two public showings (open house).

The sale of the property is arranged as an ascending-bid English auction with buyer anonymity. Bids are placed by electronic submission using digital platforms. The realtor continuously informs bidders (both active and inactive) of developments in the auction. Each and every submitted bid is legally binding as is accepting a particular bid.[10] It is possible to make conditional bids. The most typical conditions include expiration deadlines of the bid. Legally, bidders must submit bids with an expiration deadline after noon on the day of the last public showing (open house). Bids placed after that specific time may have arbitrary expiration deadlines. In practice, there is a lower bound on the expiration deadlines that are used, so that a bid is typically valid for at least 15 minutes.[11] There is no direct cost of bidding, except for the time cost of participating in an auction. However, as long as a bid is active, a bidder is legally bound to purchase the unit should the bid be accepted. Thus, very few bidders would place a bid on other units, as long as they have an outstanding non-expired and non-rejected bid. This typically creates some trade-offs for potential buyers which units to bid for in a given time period.

The seller has the option to decline any bid. If the seller declines a bid above the list price and announces a new showing without adjusting the list price, the realtor risks being reported to the authorities for knowingly mispricing the unit. The implication is that even though the list price is not a reservation price, most realtors and sellers avoid using very low list prices.

Time-on-market (TOM) in Norway is typically low, and in the capital, Oslo, it is often not more than three or four weeks. However, when the unit stays on the market for a longer time, the sales process tends to transform from an auction type to a negotiation

[9] A more detailed description can be found in Anundsen et al. (2022b).

[10] When bidders make their first bid, they typically also submit proof of financing. This practice is cloaked in some technicalities since bidders do not want to inform the realtor of the maximum financing available to them. In practice, this means that the bank confirms that the bidder has the necessary resources to back her first bid.

[11] This lower bound is due to realtors advising sellers to reject bids with extremely short expiration deadlines so that other bidders are not prevented from bidding. Anundsen et al. (2022a) study the distribution of bid lengths and show that the median bid duration is 44 minutes, while the 10^{th} percentile is 15 minutes.

between the seller and a buyer. The low TOM in Oslo is also associated with relatively quick bidder entry. Table 1 shows the distribution of the difference in entry times between the first and last bidder (based on the timing of their first bid) for Oslo rounded to the nearest hour. The median difference in entry times is 2 to 3 hours depending on the type of housing. Even at the 70^{th} percentile of transactions, the difference in entry times is less than 24 hours. Therefore, most housing auctions in Oslo tend to feature near-simultaneous entry by bidders.

Table 1: Distribution of difference in entry times between first and last bidder in Oslo, Norway (in hours).

Type of unit	10th pctl	20th pctl	30th pctl	40th pctl	50th pctl	60th pctl	70th pctl	80th pctl	90th pctl
All	0	1	1	2	3	12	18	42	119
Small apt.	0	1	1	2	3	13	20	45	124
Large apt.	0	0	1	2	2	7	17	40	139
House	0	1	1	2	2	4	15	24	93

Note: The table shows distribution of the difference between the entry times of the first and last bidder in rounded hours for transactions with at least two bidders in Oslo during 2010-2015. The entry time of a bidder is determined by the time of their first bid. Small apartments have up to 2 rooms, while large apartments have 3 or more rooms. Houses are defined as all remaining housing units, which consist of row and semi-detached houses, and single-family homes.

3 Model

We construct a stylized model of buyer entry into bidding. The model is motivated by the Norwegian institutional context, but is also applicable to housing transactions in other countries with institutional arrangements that may facilitate an auction-like format of transactions.

3.1 Basic set-up

There is a single housing unit ("the house") for sale owned by a "seller", and a large pool of potential buyers ("the buyers"). All agents in the economy are risk-neutral and utility is transferable. Motivated by the Norwegian institutional context, we abstract from dynamics, such as making several sale attempts, future re-sale possibilities, learning, and so on by modeling the housing sale as taking place in one period.[12]

The seller. We assume that the seller cares only about selling the house for a price at or above her reservation price and abstract from the costs associated with the sale process and any actions by the seller, such as setting a list price or signaling of private information, which we instead model in a reduced-form way.

[12]Such dynamic considerations would be reflected in some of our estimated parameters, however.

The seller's reservation value is given by

$$\tilde{v}(\theta, e) = \exp\{\theta + e\}, \tag{1}$$

in which θ denotes the quality of the house, and e is an idiosyncratic seller preference. For example, sellers may find their own house to be more or less valuable than the average buyer (respectively, $\bar{e}$ is positive or negative), because of a particular selection into who chooses to sell their house (for example, to move, as in Ngai and Sheedy (2019)). In addition, if a seller is relatively impatient to sell, for example, because of a moving shock, then that will be reflected in a lower reservation value. On the other hand, e may reflect a dynamic option value of selling in the future. For example, heterogeneity in buyer tastes, which we describe below, implies that seller reservation values should be positive on average ($\bar{e}$ is positive) because of an option value of selling in the future to higher valuation buyers. The dispersion in seller preferences may also be driven by seller uncertainty about the value of the house (Anenberg, 2016) or by sellers becoming discouraged over time from being unable to sell their property.[13] Finally, any behavioral biases such as reference dependence or loss aversion (Andersen et al., 2022) or differences in demographics, such as gender (Goldsmith-Pinkham and Shue, 2023), would also induce dispersion in seller reservation values. We abstract from micro-founding all these possible mechanisms that generate dispersion in seller reservation values and instead directly back out the implied mean and dispersion in the data.

The list price is assumed to be an imperfect signal of the seller's reservation value that buyers observe prior to their decision to enter bidding (see below). Specifically, we assume that the list price is given by

$$a = \tilde{v}(\theta, e) \times \eta, \tag{2}$$

in which $\ln \eta \sim N\left(\bar{\eta}, \sigma_\eta^2\right)$ reflects any differences between the list price and the seller reservation value. Therefore, we assume that there is asymmetric information between buyers and sellers regarding seller valuations. As discussed in the related literature, this opens up the possibility for signaling of reservation values and strategic behavior by the seller through list prices. We abstract from explicitly modeling these signaling incentives by directly modeling the wedge between the seller reservation value and the list price that would arise with an endogenous choice by the seller. Notice that $\overline{\eta}$ will reflect the mean signal distortion that sellers engage in, as in signal-jamming models à la Holmström (1999). As in such models, in our model buyers rationally expect such a distortion and would adjust the observed signal when making inferences about the seller reservation value (see below).

[13]This latter channel is likely more limited in our context, however, since the probability of a failed sale during our sample period is very low – between 3 and 6 percent – see Anundsen et al. (2022b).

Next, the variance σ_η^2 reflects the signal informativeness, which in a signaling model would be endogenously determined by the nature of equilibrium played, i.e., separating, semi-separating, or pooling. For example, if σ_η^2 is relatively small, then list prices would be very informative about seller valuations, as would be the case in a separating equilibrium. Conversely, if σ_η^2 is large, then list prices would be uninformative about seller valuations as would be the case in a pooling equilibrium.

The buyers. The number of potential buyers is given by B_p.[14] Buyers have preferences over the house that are comprised of a common component and an idiosyncratic component. The common component reflects quality differences between houses, such as location, type, size, and age, but also whether the house has been recently renovated, distance to local (dis-)amenities, and a good view. The idiosyncratic component reflects horizontal differences that are buyer-house specific, such as relative proximity to a buyer's workplace, relative appeal of the house, the housing layout, lighting, and interior decorations, relative preferences for certain types of local (dis-)amenities, etc. Similar to the idiosyncratic seller preference e, buyers may in addition have an idiosyncratic *buyer-specific* preference component that is not buyer-house specific. Such heterogeneity in buyer valuations may arise, for example, due to buyer impatience to buy given demographic differences or a specific family situation, due to belief heterogeneity about future house price dynamics, or due to buyers becoming more "desperate" as their search spell increases.[15] Since our empirical methodology does not allow us to separately isolate the buyer-specific from the *buyer-house* specific heterogeneity in buyer preferences, we therefore combine the two idiosyncratic components into one and directly assume that a buyer's valuation is given by,

$$w(\theta, u_i) = \exp\{\theta + u_i\} = \tilde{v}(\theta, u_i), \tag{3}$$

in which u_i denotes the idiosyncratic taste of buyer i. We assume that buyers observe θ perfectly, so there is no information asymmetries about the quality of the unit. Therefore, we abstract from any inferences buyers may draw from the number of other bidders present or from winning the auction (see below). However, in Section 7 we consider an extension of our model where we allow, in a reduced-form way, for the buyer valuation to depend on the number of other bidders that choose to participate in the auction. We also assume that u_i is private information for each buyer. This assumption is realistic, since each buyer evaluates the available information about their idiosyncratic preferences

[14] In our structural estimation, we will equate this number to the number of open-house visitors.

[15] Indeed, as Anundsen et al. (2022a) show, unsuccessful bidders in one auction tend to bid more aggressively in subsequent auctions during the same year.

privately.[16] We assume that in the population of houses, sellers, and buyers, θ, e, and the u_i's are distributed independently of each other. Moreover, θ, and e, follow normal distributions[17]

$$\theta \sim N\left(\bar{\theta}, \sigma_\theta^2\right), \tag{4}$$

and

$$e \sim N\left(\bar{e}, \sigma_e^2\right), \tag{5}$$

respectively. Finally, u_i is assumed to be distributed according to a Type I Extreme value distribution with tail probability $\Pr\{u_i > x\} = 1 - \exp\{-\exp\{-x/\sigma_u\}\}$. Therefore σ_u parameterizes the dispersion in buyer idiosyncratic tastes. For that reason we refer to σ_u as the "dispersion" in buyer-specific tastes below. The assumption of a Type I Extreme value distribution for u_i is natural in our context. The distribution is the limiting distribution for the maximum of a large number of normally distributed random variables. On the other hand, buyers that choose to come to a viewing usually inspect a large number of houses via an online search platform before choosing to go and see their most preferred house(s).

We define

$$\tilde{a} \equiv \ln a - \theta - \bar{\eta} = e + \ln \eta - \bar{\eta}, \tag{6}$$

so that

$$\tilde{a}|e \sim N\left(e, \sigma_\eta^2\right) \tag{7}$$

Therefore, given these distributional assumptions, the informational assumptions for the buyers, and the assumption that buyers are fully rational, it follows that the posterior belief about e for each buyer, given the list price a is

$$e|a \sim N\left(\frac{1/\sigma_e^2}{1/\sigma_e^2 + 1/\sigma_\eta^2}\bar{e} + \frac{1/\sigma_\eta^2}{1/\sigma_e^2 + 1/\sigma_\eta^2}\tilde{a}, \frac{1}{1/\sigma_e^2 + 1/\sigma_\eta^2}\right). \tag{8}$$

Note that this posterior distribution is independent of the mean list price wedge $\bar{\eta}$.

[16] Note that in our model we do not make a distinction between a buyer's valuation and her willingness-to-pay for a house. Therefore, we abstract from any financial constraints that may create a wedge between the two. Our data does not allow us to distinguish between heterogeneity in valuations and heterogeneity in willingnesses-to-pay, so our structural estimates of buyer preference heterogeneity will be a combination of the two.

[17] Assuming a log-normal value for quality matches well the observed distributions of appraisals and sale prices in the data. The assumption of normally distributed seller-specific preference is made for tractability, since it simplifies the posterior distribution of e, given the observed list price a.

Price determination

After observing θ, a, and their u_i's, potential buyers choose simultaneously whether to enter a bidding stage. To enter that stage, a buyer must pay an entry cost $c > 0$. If the buyer does not pay the entry cost, she collects an outside option, which is normalized to 0. Therefore, the cost c will reflect both the true cost associated with the process of buying a house, as well as an opportunity cost arising from the buyer's true outside option. After paying the cost c, the buyer learns the true value of e.

We let $\tilde{B}$ denote the number of buyers that enter the bidding stage. Below, it will also be useful to define $B = \tilde{B} - 1$ as the number of other buyers entering the bidding stage from the perspective of a buyer that has chosen to enter. We assume that a buyer who chooses to enter observes the realization of B perfectly, so that she knows how many opponents she is bidding against.[18]

If $\tilde{B} = 0$, then no transaction takes place. If $\tilde{B} = 1$ (so $B = 0$), there is no auction, and instead we assume that if the surplus from trading is positive, then the price is determined via a negotiation process. In particular, we assume that the buyer makes a take-it-or-leave-it offer to the seller, so the price equals the seller's reservation value.[19] If $\tilde{B} > 1$ (or $B > 0$), we assume that the price is determined in a second-price auction with a reservation price of $\tilde{v}(\theta, e)$.

Notice that given the *ex ante* information asymmetry, it is possible that even if $\tilde{B} > 0$, no trade takes place, since *ex post*, all buyers who enter the bidding stage may have lower valuation than the seller reservation value. This will be the case if $\boldsymbol{u}_{(\tilde{B})} < e$, where $\boldsymbol{u}_{(\tilde{B})}$ denotes the largest order statistic of $\boldsymbol{u} = (u_1, u_2, \ldots, u_{\tilde{B}})$. We can call this a situation of *informational mismatch.* Whenever there is no informational mismatch, and given the specific assumptions on the transaction process, we can write the transaction price as

$$p\left(\theta, \boldsymbol{u}, e, \tilde{B}\right) = \begin{cases} w(\theta, e) & , \ \tilde{B} = 1 \\ w\left(\theta, \max\left\{\boldsymbol{u}_{(B)}, e\right\}\right) & , \ \tilde{B} > 1 \end{cases}, \tag{9}$$

where $\boldsymbol{u}_{(B)}$ is the second (largest) order statistic of $\boldsymbol{u}$. Figure 1 presents a time-line of events in the model.

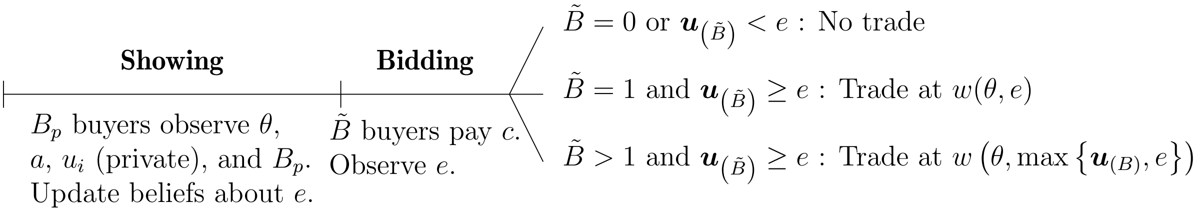
Buyer payoffs

Let $W(B, \theta, e, u_i)$ denote the expected payoff for buyer i who has entered the bidding stage, given that a total of B other buyers are present at that stage and given that $u_i > e$. Let $\boldsymbol{u}_{-i} = (u_1, u_2, \ldots, u_{i-1}, u_{i+1}, \ldots, u_{\tilde{B}})$ denote the vector of buyer-specific

[18] This is without loss of generality given the second-price auction assumption and given that buyers are risk neutral in the price (McAfee and McMillan, 1987).

[19] Allowing for price determination via Nash bargaining leads to structural estimates of the bargaining strength of the buyer close to one.

Figure 1: Model time-line.



valuations that exclude buyer i's valuation. Then, in the case when $B = 0$, we have,

$$W(0, \theta, e, u_i) = w(\theta, u_i) - w(\theta, e). \tag{10}$$

In the case when $B \geq 1$, we have

$$W(B, \theta, e, u_i) = \Pr\left\{(\boldsymbol{u}_{-i})_{(B)} < u_i\right\} E\left[w(\theta, u_i) - p(\theta, \boldsymbol{u}, e, B+1) \middle| (\boldsymbol{u}_{-i})_{(B)} < u_i\right], \tag{11}$$

or using equation (9),

$$W(B, \theta, e, u_i) = \Pr\left\{(\boldsymbol{u}_{-i})_{(B)} < u_i\right\} \times \left\{w(\theta, u_i) - E\left[w\left(\theta, \max\left\{(\boldsymbol{u}_{-i})_{(B)}, e\right\}\right) \middle| (\boldsymbol{u}_{-i})_{(B)} < u_i\right]\right\}. \tag{12}$$

It is straightforward to show that W is increasing in θ and u_i and decreasing in e, and B.

Lemma 1. *A buyer's expected payoff W in the bidding stage is increasing in θ and u_i, and is decreasing in e and B.*

Proof. See Appendix B. □

Buyer entry decisions

Since the idiosyncratic preferences u_i are private information, buyers do not know the exact number of other buyers that will enter the bidding stage at the time of their entry decision. Instead, they (rationally) anticipate that this number will follow a certain (endogenously determined) distribution. Moreover, by Lemma 1, buyers will choose whether to enter the bidding stage according to a cutoff rule. To see this, note that a buyer with idiosyncratic taste u will choose to enter iff

$$E_B\left[\mathbb{1}_{\{u>e\}} W(B, \theta, e, u) \,|a\right] \geq c, \tag{13}$$

in which $E_B[.]$ denotes expectation with respect to the (endogenously determined) distribution of B.[20] Since W is increasing in u, it follows that the left-hand side of Eq. (13) is also increasing in u, so that there exists a unique idiosyncratic valuation threshold, denoted by $\hat{u}(\theta)$, which satisfies

$$E_B\left[\mathbb{1}_{\{\hat{u}(\theta,a)>e\}} W\left(B,\theta,e,\hat{u}(\theta,a)\right)|a\right] = c, \tag{14}$$

such that a buyer enters iff $u_i \geq \hat{u}(\theta,a)$. We can further simplify Eq. (14) using the observation that a buyer with the threshold valuation $u_i = \hat{u}(\theta,a)$ has the highest valuation among $B+1$ buyers (for $B \geq 1$) with zero probability. Put differently, a buyer with the marginal idiosyncratic valuation $\hat{u}(\theta,a)$ never expects to win an auction, and hence, always receives a payoff of zero in that contingency. The only contingency when the buyer receives a positive payoff (that would compensate for her entry cost c in expectation) is when there are no other buyers, i.e., $B = 0$ and $e < \hat{u}(\theta,a)$, so that there is a positive surplus from trading. Therefore, Eq. (14) becomes

$$\begin{aligned} E_B\left[\mathbb{1}_{\{\hat{u}(\theta,a)>e\}} W\left(B,\theta,\hat{u}(\theta)\right)|a\right] &= \Pr\{e < \hat{u}(\theta,a)|a\} \Pr\{B = 0|a\} \times \\ &\{w(\theta,\hat{u}(\theta,a)) - E\left[\tilde{v}(\theta,e)|a, e < \hat{u}(\theta,a)\right]\} = c. \end{aligned} \tag{15}$$

Hence, the expected payoff for the marginal buyer who enters the bidding stage equals the probability that trade will take place, multiplied by the probability that there will be a negotiated sale and the difference between the buyer's valuation and her expectation of the seller's valuation given the list price.

3.2 Buyer entry game

Given this set-up, we can define a symmetric (Bayesian) Nash equilibrium of the buyer entry game as follows.

Definition. *Given values of θ, a, and B_p, a symmetric (pure strategy) Bayesian Nash Equilibrium of the buyer entry game consists of a buyer entry decision $\chi(u) \in \{0,1\}$ and a distribution of entering buyers, $\tilde{B}$, such that $\chi(u) = 1$ iff condition (13) is satisfied, and the distribution $\tilde{B}$ reflects the entry decision $\chi(u)$.*

Given that entry follows the cutoff rule from Eq. (14), it follows that prior to drawing the idiosyncratic preferences, the probability, q, of any given buyer entering the bidding stage is given by

$$q(\theta,a) = \Pr\left\{E_B\left[\mathbb{1}_{\{u_i>e\}} W\left(B,\theta,e,u_i\right)|a\right] \geq c\right\} = \Pr\{u_i \geq \hat{u}(\theta,a)\}, \tag{16}$$

[20]We assume that a buyer who is indifferent between entering and not chooses to enter the bidding stage.

with $\hat{u}(\theta, a)$ satisfying Eq. (14). Since idiosyncratic draws are i.i.d., the (ex ante) distribution of entering buyers, $\tilde{B}$, is therefore a Binomial distribution with parameters B_p and $q(\theta, a)$. Similarly, the distribution of *other* buyers entering the bidding stage, B, is Binomial with parameters $B_p - 1$ and $q(\theta, a)$. We summarize these observations in the following equilibrium characterization result.

Proposition 1. *Given values of θ, a, and B_p, there is a unique symmetric pure strategy Bayesian Nash Equilibrium of the buyer entry game characterized by:*

- *A cutoff valuation $\hat{u}(\theta, a)$ that satisfies Eq. (14), such that a buyer enters and bids iff $u \geq \hat{u}(\theta, a)$.*
- *An (ex ante) distribution of entering buyers which is Binomial with parameters B_p and $q(\theta, a)$, where q satisfies Eq. (16).*

Figure 2 illustrates the shape of the cutoff rule $\hat{u}$ in the top row (that is its dependence on θ and a) and its dependence on model parameters in the remaining panels. Not surprisingly, given Lemma 1, $\hat{u}$ is decreasing in θ. Intuitively, given a fixed entry cost for bidding, a house that is more valuable (irrespective of the buyer's own idiosyncratic valuation) raises the buyer's expected payoff from bidding for the house and thus induces entry by buyers with lower idiosyncratic valuations. Put differently, higher quality houses attract more bidders. The cutoff $\hat{u}$ is also increasing in a, so that a higher list price acts on a buyer's entry decision the same way as lowering the quality of the house. This is because a signals a higher seller-specific preference e to buyers. Raising the average seller-specific preference, $\bar{e}$, has a similar effect on $\hat{u}$ (bottom, right panel). Also, unsurprisingly, a higher bidding cost, c, raises the cutoff value $\hat{u}$, since buyers must expect to have a higher payoff from bidding to counter the higher bidding cost. $\hat{u}$ is also increasing in the number of potential buyers, B_p. Intuitively, a higher value of B_p raises the expected number of bidders, $\tilde{B}$, which lowers the payoff to any single buyer from entering the bidding stage and raises the cutoff $\hat{u}$.

More interestingly, $\hat{u}$ is increasing in the dispersion of buyer idiosyncratic tastes. Intuitively, a higher dispersion of buyer tastes raises the probability of having an extremely high idiosyncratic valuation, which, in turn, raises the probability of any single buyer entering the bidding stage. This results in a higher number of expected buyers, similarly to the effect of B_p, thus, also raising the cutoff.

Increasing the dispersion of the list price wedge has an ambiguous effect on $\hat{u}$, since it depends on the relative magnitude of the list price. For a low list price that lets the buyer update towards a lower value of e than the prior mean, higher dispersion σ_η, which makes the list price less informative about the seller reservation value, implies that the buyer relies more on her prior mean (i.e., $\bar{e}$). Consequently, the buyer expects a higher reservation value, and the value of $\hat{u}$ increases. The opposite happens when the list price is high and the dispersion of the list price wedge goes up.

A higher dispersion of the seller-specific preference e has several effects. First, similar to the effect of changing σ_η, it affects the inference of the buyer, making the buyer weight more the list price when inferring e. As with the effect of changing σ_η, the relative value of the list price would matter for the direction of this effect. Second, it makes more extreme values of e more likely by moving mass to the tails of the seller-specific taste distribution. Depending on the value of $\hat{u}$ relative to a, this may increase or lower the expected payoff from entering the bidding stage. In practice, however, this effect is quantitatively small, as shown in Figure 2 (bottom, left panel).

4 Data and Estimation

4.1 Data

We use bidding-logs and information on open-house showings from all sales handled by two of the largest real estate agencies in Norway, DNB Eiendom and Krogsveen over the period 2010–2015. We consider the Oslo housing market, excluding units that belong to a housing co-operative ("co-op units").[21]

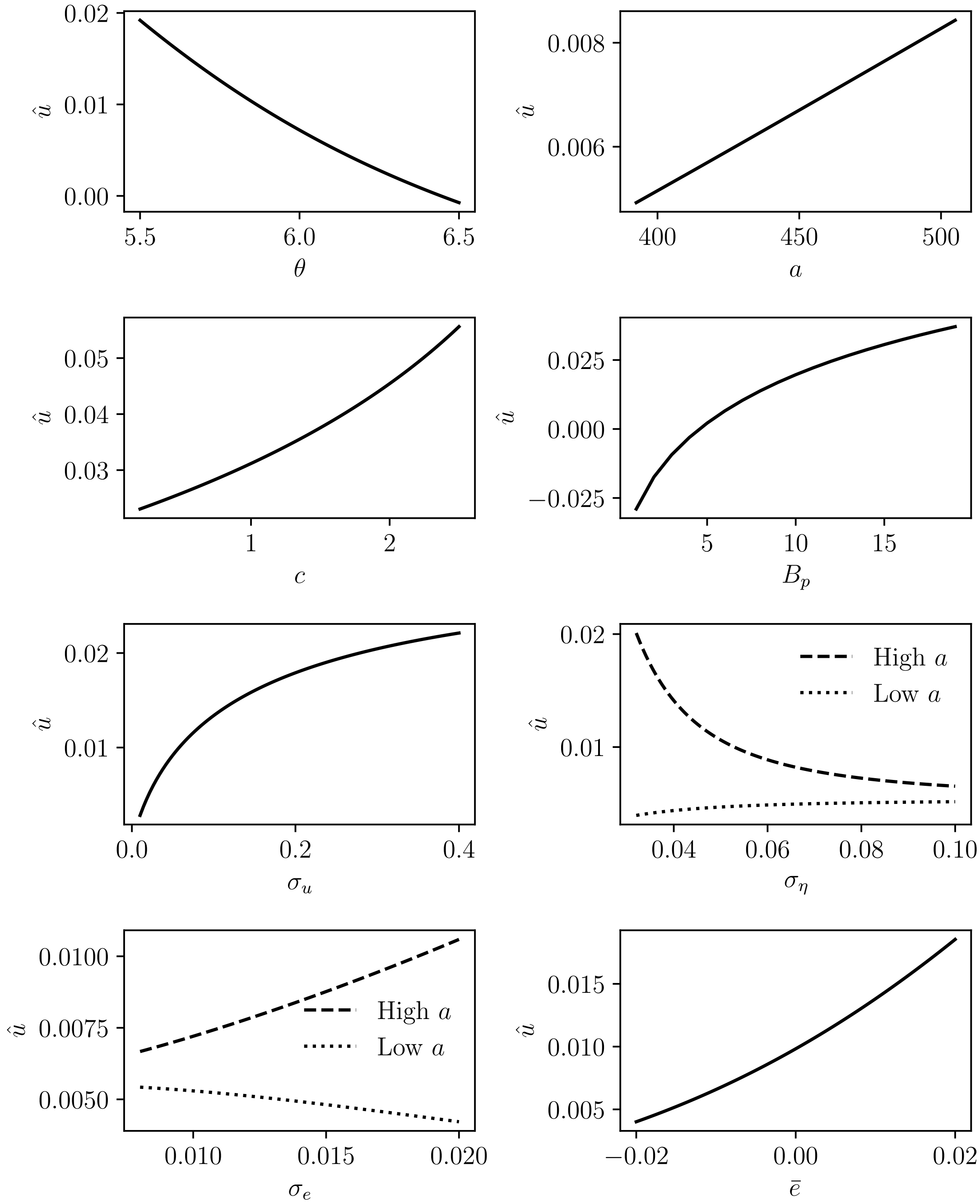
The data sets contain information on each bid placed in every housing sale handled by these real estate agencies. The data sets also include a unique bidder id, which allows us to compute the number of bidders in each auction. Additionally, both data sets contain information on the list price, the exact sales date, the exact date when the unit was listed for sale, attributes of the unit (size, address, unit type).[22]

We use the bidding-level data to extract information on time-on-market, sale prices, list prices, and the spread between sale prices and list prices. In addition, we construct measures of the number of open-house visitors, and number of bidders. Table 2 summarizes the data. Since our structural model is static, it is best suited to describe a single attempt at selling a house. Moreover, we are interested in the first such attempt, since the first attempt reflects the bulk of the transactions that take place. We identify the

[21]We exclude co-operatives from our analysis, since the selling process for co-op owned units differs from that of self-owned units, and thus from our model in Section 3. Specifically, co-ops always carry a right of first refusal, which gives the option for members of the co-op (based on a seniority ranking) to purchase a unit at the highest accepted bid without taking part in the bidding. Bidders participating in an auction for a co-op unit, therefore, also have to take into account the possibility that they may not get to buy the unit even if they placed the highest bid and the seller accepted this bid (McKay and Riis, 2023).

[22]Table A.1 in Appendix A describes the data trimming we perform. For most of the analysis, we use data from both firms. However, the Krogsveen data set has information on the number of people showing up at the public showing (the open house), as well as how many showings have been arranged before a sale takes place. That information is not contained in the DNB data, so we use the Krogsveen data for all calculations involving number of open-house visitors and number of showings.

Figure 2: Comparative statics for $\hat{u}$.



Note: Parameterized with $\sigma_u = 0.0297$, $\sigma_e = 0.0140$, $\sigma_\eta = 0.0638$, $c = 0.1040$, $\bar{e} = -0.0101$, $\bar{\eta} = -0.0154$, $\theta = 6.0332$, and $B_p = 6$. High (low) ask prices, a, specified by increasing (decreasing) e by $9\sigma_e$.

first sale attempt as the 4-week period from the listing date. We choose this cutoff, since the estimated hazards of receiving a bid flatten after these periods, as Figure A.1 in the Appendix shows. Therefore, any auction-like transaction process with multiple bidders and bids likely take place prior to these cutoffs, and if a housing unit does not sell by this period, it either goes through a subsequent re-listing, resulting in a new sale attempt or continues receiving sequential offers from single buyers, which is a transaction process that our model does not represent well. The probability of receiving a bid at the first attempt is 87 percent, and the probability that a sale occurs at the first attempt is 81 percent. Conditional on receiving at least one bid, the probability of selling at the first attempt is 94 percent.[23]

Table 2: Summary statistics for auction-level data. Segmentation on one versus multiple bidders, 2010–2015

	Full sample		One bidder		Multiple bidders	
Variable	Mean	Std.	Mean	Std.	Mean	Std.
Sell (in 1,000 USD)	627.07	288.98	640.31	293.65	622.56	287.26
List (in 1,000 USD)	594.39	278.09	636.1	292.62	580.19	271.53
Square footage	915.55	488.34	941.45	492.03	906.73	486.8
Sell-List spr. (in %)	6.11	8	.85	5.07	7.9	8.03
No. bidders	2.98	2.09	1	0	3.66	2.02
No. bids	9.83	7.82	2.8	1.84	12.23	7.64
No. open-house visitors	11.61	8.91	5.53	4.09	13.57	9.16
Bidders per open-house visitor	.33	.2	.3	.24	.34	.19
No. public showings	1.97	.98	1.9	1.19	1.99	.9
No. visitors per open-house	6.81	6.08	3.23	2.74	7.86	6.38
Time-on-market (days)	13.69	7.3	13.79	8.1	13.66	7
Perc. with sell < list	18.53		39.09		11.54	
Perc. apartment	78.37		78.89		78.2	
Prob. sell at first att.	0.82					
Prob. bid at first att.	0.87					
Prob. sell if bid at first att.	0.94					
No. auctions	12,044		2,492		9,552	

Note: The table shows summary statistics for auction-level data from DNB Eiendom and Krogsveen over the period 2010–2015. Since the data from DNB Eiendom do not contain information on number of open-house visitors, these measures are calculated using only data from Krogsveen. We distinguish between units sold in one-bidder auctions and units sold in multiple-bidder auctions. For each of the segments, the table shows the mean 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 2010–2015, in which the exchange rate was $USD/NOK = 0.1639$

[23] Figure A.2 in the Appendix displays time series for four key variables: the mean sell-ask spread, time-on-market, number of bidders, and the percentage of units that are sold at the first attempt.

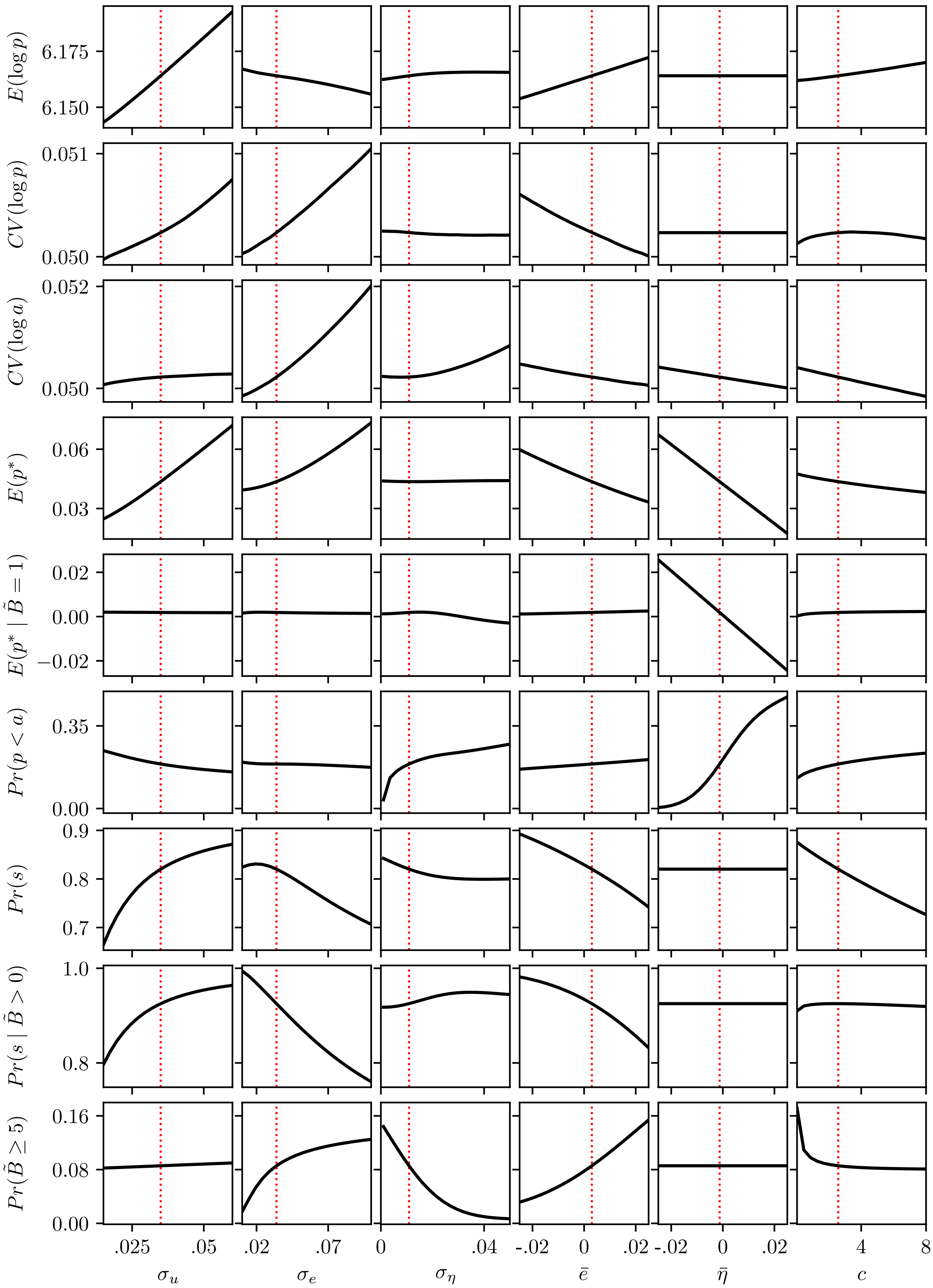
4.2 Estimation method

Next, we describe our estimation procedure and a number of parametric assumptions we make. Since our data span a large number of different locations, types of housing, and time periods, and each of these characteristics would have a direct effect on the underlying distribution of quality, the distribution of potential buyers, and potentially all other model parameters, we define a number of sub-markets, or segments, and let a number of parameters of the estimated model vary by segment. Specifically, we define segments based on housing type and size, and time period. For time periods, we consider separately every year in our sample, while for housing type and size we define three categories, namely Small apartments, Large apartments and Houses. Small apartments have up to 2 rooms, while large apartments have 3 or more rooms.[24] Houses are defined as all remaining housing units, which consist of row houses, semi-detached houses, and single-family houses.

We estimate the model parameters using Simulated Method of Moments.[25] Specifically, for each segment we construct a large number of artificial data-sets with size equal to the number of observed sales in each segment. Each observation in these artificial data-sets corresponds to a distinct instance of the buyer entry game described in Section 3. Therefore, for each distinct dwelling in the artificial data-sets we draw a unique combination of quality θ, seller reservation value e, list price a, as well as the number of potential buyers, B_p, and a vector of idiosyncratic preferences for these buyers, $\boldsymbol{u}$. Based on these factors, we compute the entry cutoff $\hat{u}$ according to Eq. (14), the set of potential buyers that enter the bidding stage given this cutoff, and the realized price, p, if a sale takes place, according to Eq. (9).

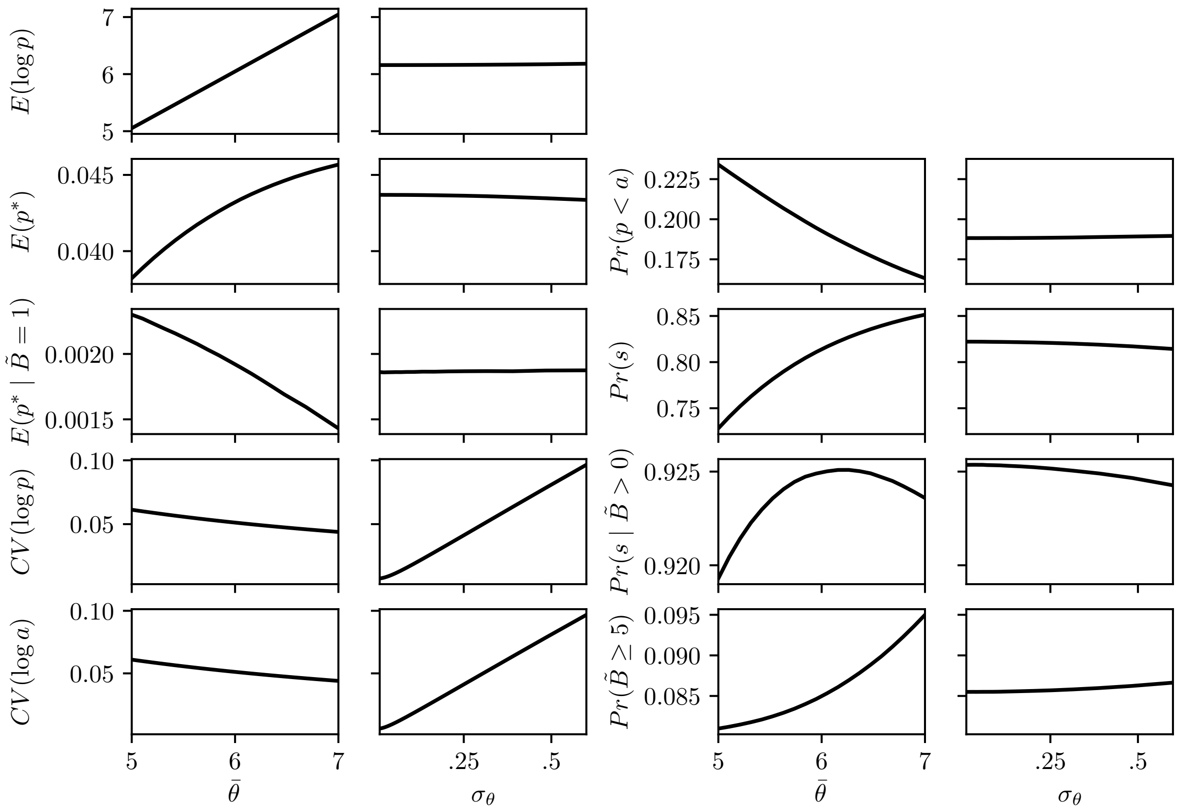
We draw the number of open-house visitors, B_p, from each segment's empirical distribution of open-house visitors. [26] In our estimation, we let the dispersion and mean of quality, θ, vary by segment, while for the remaining parameters – the dispersion in buyer idiosyncratic tastes, σ_u, the mean and dispersion of seller reservation values, ($\bar{e}$ and σ_e), the mean and dispersion of the log of the list price wedge, η, ($\bar{\eta}$ and σ_η), and the entry cost c – we impose time-invariance.[27]

Figure 3: Moment comparative statics.



Note: s denotes the sell probability. p^* denotes the price premium, $\log p - \log a$. The moments are computed for the following parameter values: $\sigma_\theta = 0.3064$, $\sigma_u = 0.0350$, $\sigma_e = 0.0339$, $\sigma_\eta = 0.0109$, $\bar{\theta} = 6.1175$, $\bar{e} = 0.0030$, $\bar{\eta} = -0.0012$, and $c = 2.5804$, also given by the vertical dotted lines.

Figure 4: Moment comparative statics for $\bar{\theta}$ and σ_θ.



Note: s denotes the sell probability. p^* denotes the price premium, $\log p - \log a$. The moments are computed for the following parameter values: $\sigma_\theta = 0.3064$, $\sigma_u = 0.0350$, $\sigma_e = 0.0339$, $\sigma_\eta = 0.0109$, $\bar{\theta} = 6.1175$, $\bar{e} = 0.0030$, $\bar{\eta} = -0.0012$, and $c = 2.5804$, also given by the vertical dotted lines.

4.3 Moments and identification

Next, we discuss identification in our estimation framework. Formally, if we define a moment function from the space of parameters to the space of moments, (local) identification requires that the Jacobian matrix of the moment function evaluated at the true parameter values has rank equal to the number of parameters. More informally, each parameter should change the moments in a unique way. In practice, the moments have to also be "informative" about the parameters, so that the moment function is not close to flat around the true parameter values. These two considerations guide our choice of moments.

For each segment, we use 9 moments: (i) the mean (log) sale price ($E(\log p)$), (ii) the coefficient of variation of (log) sale price ($CV(\log p)$) and (iii) (log) list price ($CV(\log a)$), (iv) the mean price premium, defined as the difference between the mean (log) sale price and (mean) (log) list price ($\log p - \log a$), (v) and the mean price premium given only one bidder, (vi) the probability that the sale price is lower than the list price, as well as the sale probability – both (vii) unconditional, and (viii) conditional on there being at least one bidder. Finally, (ix) we target the probability of a contested auction, defined as an auction with 5 bidders or more. Overall, we have 54 moments per unit type and 18 parameters, so our model is substantially over-identified.

Figure 3 shows how these moments respond to the model parameters for a specific time period for the time-invariant parameters σ_u, σ_e, σ_η, and $\log c$, while Figure 4 contains a similar set of moment comparative statics plots for the quality parameters $\bar{\theta}$ and σ_θ. Next, we discuss briefly which moments are informative for each parameter and provide brief intuition for these effects based on the mechanics of our model.

For σ_u the informative moments are the mean and coefficient of variation of the sale price, the price premium, and also the sale probability. Intuitively, a higher dispersion of idiosyncratic tastes increases both the mean price and price premium, since it becomes more likely for several buyers with relatively high valuations to enter bidding. It also increases the sale probability due to selection effects, since it is easier for a larger set of housing units to attract a buyer with a sufficiently high valuation. Finally, price dispersion also increases, since buyers have more idiosyncratic tastes but also because of the aforementioned selection effects, whereby more lower quality units can also sell.

For σ_η the most informative moments are the probability that the sale price is below the list price, the sale probability, and the probability of a contested auction. Intuitively,

[24] A two-room apartment will have two livable rooms in addition to any bathrooms, kitchen, hallways, or pantries.

[25] See the Appendix for details about the estimation algorithm.

[26] Figure A.3 in the Appendix plots this distribution for small apartments in 2011 and houses in 2014. The probabilities are estimated by bins of number of open-house visitors. In the simulations, the probability of drawing any given number of open-house visitors within each bin is assumed uniform.

[27] We also perform the estimation by letting all parameters vary over time. The parameter estimates for this estimation are similar to our baseline parameters – see Table A.4 in the Appendix.

for the effect on sale probability, by Eq. (8), a higher dispersion σ_η increases the posterior variance about the seller's reservation value, thus worsening the quality of information available to potential buyers when they make their bidding entry decisions. Consequently, there are more instances of informational mismatch, whereby buyers with idiosyncratic preferences lower than the seller's true reservation value enter the bidding stage, which reduces the share of transactions. Regarding the effect on the probability that sale price is below the list price, if there is no dispersion in η, the sale price can never be below the list price, since the list price equals the seller reservation value. With some dispersion in η the list price and the seller reservation value are decoupled, so that it is possible that the seller reservation value (and hence the sale price given at least one bidder with sufficiently high valuation) lies below the list price.

A higher value of σ_e has a similar effect on the sale probability and list price dispersion to that of a higher value of σ_η for similar reasons. It also increases the price premium, since it lowers the average (log) list price of units that end up transacting. Finally, it increases price dispersion, since having more units with more extreme values of the seller-specific preference increase the probability that units sell with only one bidder. For these units, the price equals the seller reservation price, so a higher dispersion in seller-specific preferences mechanically increases price dispersion for those units.

A higher entry cost, c, affects many of the moments but most notably the probability of sale, since a higher value of c increases the cutoff $\hat{u}$ (see Figure 2), which, *ceteris paribus*, lowers bidder entry and the sale probability. An increase in the average seller-specific preference, $\bar{e}$, reduces the sale probability, since it reduces bidder entry. It also increases the average sale price, since for all objects with a negotiated sale (i.e., only one bidder with valuation above the seller reservation price) the price directly depends on the seller reservation price. However, a higher $\bar{e}$ decreases the price premium, since the average list price is more responsive to $\bar{e}$ than the average sale price. $\bar{e}$ also affects price dispersion negatively. This is due to a selection effect the average seller reservation price exerts on the quality distribution of objects sold. Turning to the list price wedge, a change in $\bar{\eta}$ leads to a mechanical change in moments involving the list price. For example, a higher value of $\bar{\eta}$ decreases the price premium, since it increases the average (log) list price. It also increases the share of objects that sell below the list price.

Finally, regarding the quality distributions, the average quality parameter $\bar{\theta}$ has an effect on all moments, but particularly so on the average sale price, the probability of sale, as well as the probability that the sale price is below the list price. For the dispersion of quality, there are only two particularly informative moments: the dispersion in the sale and list prices.

5 Results

5.1 Parameter estimates and model fit

Table 3 presents the parameter estimates from our baseline estimation. Table 4 shows the simulated moments at the estimated parameters together with corresponding data moments for segments with the best and worst fit.[28] The simulated moments are for the most part very close to their data counterparts, even for the segments with the worst fit. This is reassuring, since there is substantial over-identification in our estimation.

Table 3: Parameter estimates.

	Small apt.	Large apt.	House
σ_u	0.0350 (0.0081)	0.0315 (0.0160)	0.0465 (0.0106)
σ_e	0.0339 (0.0080)	0.0353 (0.0157)	0.0232 (0.0122)
σ_η	0.0109 (0.0073)	0.0121 (0.0130)	0.0261 (0.0111)
$\bar{e}$	0.0030 (0.0070)	0.0031 (0.0119)	0.0289 (0.0094)
$\bar{\eta}$	-0.0012 (0.0072)	-0.0009 (0.0134)	-0.0010 (0.0100)
c	2.5804 (0.0061)	3.3942 (0.0111)	8.7316 (0.0095)

Note: Standard errors in parenthesis. σ_u, σ_e, σ_η, $\bar{e}$, $\bar{\eta}$, and c are constrained to vary only by housing type, whilst remaining parameters may vary between years.

We estimate a sizable dispersion parameter for buyer idiosyncratic tastes across all housing types with a slightly higher value for houses relative to apartments.[29] The estimated dispersion in seller-specific preferences is comparable across housing types and slightly smaller than the dispersion in buyer-specific tastes. The average of the seller-specific preference, $\bar{e}$, is estimated to be very close to zero apart from houses where it is slightly positive. Therefore, with the possible exception of houses, there are no systematic differences between average seller log reservation prices and the dwelling's underlying quality (though there is sizable dispersion in seller-specific preferences).

The estimated cost of bidding entry is about twice as high for houses compared to apartments. This is to be expected, since transaction costs (in the form of brokerage fees and fees paid to the state) scale up with the average value of the property type.[30] Finally, in terms of the list price wedge, η, there is substantial dispersion in η, reflecting a partial disconnect between list prices and seller valuations, and suggesting that list prices are imperfect signals for seller reservation prices. Moreover, the estimated mean wedge is negative though very close to zero, which implies that we cannot reject a zero mean bias

[28]Table A.2 in the Appendix includes the estimated parameters for the distribution of θ, while Table A.3 in the Appendix shows the simulated and data moments for all segments.

[29]These dispersion parameters translate into a distribution with interquartile range of between 0.05 and 0.07.

[30]In Norway, there is a 2.5 percent stamp duty, to be paid upon each transaction. Furthermore, all placed bids are binding, so that a buyer who bids always assumes that they may acquire the property (and pay the associated monetary transaction costs) when submitting a bid.

in the list price wedge.

Table 4: Target moments for segments with best and worst fit.

	Best		Worst	
Moment	Model	Data	Model	Data
$E[\log p]$	6.752	6.757	6.067	6.074
$E[p^*]$	0.039	0.057	0.041	0.070
$E[p^* \mid B = 1]$	0.008	0.007	0.002	0.014
$CV(\log p)$	0.046	0.046	0.053	0.053
$CV(\log a)$	0.046	0.046	0.053	0.054
$Pr(sale)$	0.747	0.753	0.806	0.856
$Pr(sale \mid \tilde{B} > 0)$	0.923	0.915	0.920	0.949
$Pr(\tilde{B} \geq 5)$	0.109	0.177	0.076	0.190
$Pr(p \leq a)$	0.255	0.190	0.200	0.129
Segment		House, 2013		Small apt., 2012
Loss		0.0164		0.2693

Note: The table shows targeted moments in the baseline estimation for individual segments with the greatest and smallest losses. $p^* = \log p - \log a$.

5.2 Validation

In Table 5, we compare the performance of the model against a number of non-targeted moments, and we find that the estimated model gets fairly close to most non-targeted data moments. However, the average ratio of bidders to open-house visitors tends to be a bit higher than in the data. Similarly, the standard deviation of number of bidders is somewhat higher than in the data. One explanation for these discrepancies is that the observed data on number of bidders is naturally truncated given that in reality bidding entry is sequential rather than simultaneous as in our model, and the auction format in the data is of a dynamic ascending-bid (English) type rather than a simultaneous second-price auction. Therefore, in the data, only lower valuation bidders who enter early would be reflected in the bidding records, whereas lower valuation bidders who come late to the bidding would tend to choose not to bid at all (and hence not appear in the bidding records), if the current highest bid is already above their valuation.

Next, we validate the estimated model against a direct measure of buyer valuations. This is a particularly important validation of our model, since one of the main aims of the estimation is to understand the contribution of buyer preference heterogeneity to house prices. Specifically, we use the detailed bidding information from our data set to construct lower and upper bounds on the valuations of bidders who participate in auctions (i.e., when there are at least two bidders) and who do not end up submitting the highest final bid (i.e., they "lose" the auction). The lower bound is the highest bid that a losing bidder submits in the bidding log, while the upper bound is the bid that is submitted by another

Table 5: Non-targeted model moments.

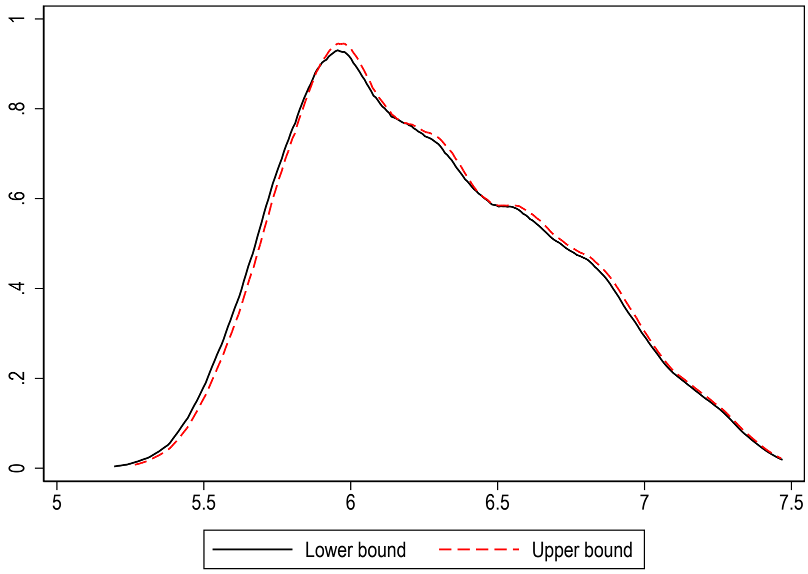
#	Type	Year	$E[\tilde{B}]$ Model	$E[\tilde{B}]$ Data	$SD(\tilde{B})$ Model	$SD(\tilde{B})$ Data	$Pr(\tilde{B}=1)$ Model	$Pr(\tilde{B}=1)$ Data	$E[\tilde{B}/B_p]$ Model	$E[\tilde{B}/B_p]$ Data
1	Small apt.	2010	2.426	2.684	2.010	1.976	0.372	0.296	0.550	0.429
2	Small apt.	2011	2.763	3.052	2.577	1.999	0.339	0.215	0.522	0.406
3	Small apt.	2012	2.911	3.222	2.759	2.308	0.316	0.222	0.510	0.371
4	Small apt.	2013	2.761	2.684	2.430	1.921	0.326	0.310	0.520	0.377
5	Small apt.	2014	4.411	2.999	4.620	2.109	0.213	0.250	0.386	0.308
6	Small apt.	2015	4.975	3.258	5.123	2.372	0.176	0.247	0.357	0.238
7	Large apt.	2010	2.604	2.681	2.485	1.728	0.376	0.251	0.507	0.397
8	Large apt.	2011	2.852	3.097	2.906	1.964	0.351	0.221	0.499	0.373
9	Large apt.	2012	2.739	3.154	2.654	2.200	0.351	0.233	0.509	0.343
10	Large apt.	2013	2.691	2.789	2.492	2.064	0.354	0.266	0.507	0.358
11	Large apt.	2014	4.022	2.717	4.036	1.717	0.240	0.254	0.375	0.274
12	Large apt.	2015	4.651	2.837	4.767	1.835	0.202	0.277	0.349	0.238
13	House	2010	3.259	3.211	3.362	2.108	0.353	0.218	0.463	0.367
14	House	2011	3.089	2.828	3.303	1.964	0.374	0.267	0.480	0.319
15	House	2012	3.095	3.019	3.047	2.017	0.356	0.231	0.473	0.345
16	House	2013	3.378	2.869	3.534	2.036	0.328	0.271	0.456	0.317
17	House	2014	4.852	2.915	5.095	1.966	0.249	0.245	0.385	0.274
18	House	2015	5.725	3.150	5.958	2.097	0.207	0.249	0.355	0.218

Note: The table shows non-targeted moments in the baseline estimation for individual segments. $p^* = \log p - \log a$.

bidder subsequent to that bidder's highest bid. The reason for constructing both lower and upper bounds to the bidder valuation rather than treating the bidder's highest bid as her valuation is that jump bidding and counter-bidding are prevalent in the auction bidding logs. Indeed, around 25 percent of bids following a losing bidder's highest bid have a bid increment of at least 50,000 Norwegian kroner, which represent more than 1 percent of the average sale price of units in our sample. Figure 5 plots the distribution of the logged lower and upper bounds of losing bidder valuations, constructed as explained above. As the figure shows, the upper and lower bounds are fairly close. Moreover, unconditionally, the upper-bound distribution is essentially a rightward shifted version of the lower-bound distribution.

Next, Table 6 compares the model and data-derived bidder valuation distributions based on the mean and standard deviation of the log valuation. We make this comparison by housing type and year. Overall, the model-generated bidder valuations have means and standard deviations that are very close to the data generated moments, particularly for the upper bound measures (denoted by UB in the table). For example, the standard deviation of the log losing bidder valuation is between 0.29 and 0.45 in the model and

Figure 5: Losing bidder valuations.



Note: The graph plots the lower and upper bounds of losing bidder valuations in the data, all in logs. The lower bound is based on the highest bid that a losing bidder submits in the bidding log, while the upper bound is based on the bid that is submitted by another bidder subsequent to the bidder's highest bid.

between 0.28 and 0.47 for the upper bound measure.[31]

Finally, similar to the data-derived distribution of bidder valuations, we use our detailed bidding logs data to compute a proxy for the seller reservation price by considering bidding logs in which the seller makes a counter-bid, i.e., an offer to the bidder. Specifically, we take the first counter-bid the seller makes in that case. In our model, we equate this to either (i) a situation with entry of only one bidder or (ii) a situation with multiple bidder entry, whereby at most one bidder has a valuation above the seller reservation value. These are precisely the situations in the data, in which a negotiated sale occurs. Table 7 compares the mean and standard deviation of the model generated log seller reservation value given these events, and the mean and standard deviation of the log of the seller counter-bid in the data. The model-generated log seller reservation value has a consistently lower mean compared to the data-generated counterpart but a very similar standard deviation. The discrepancy in the mean values likely reflects strategic aspects of the negotiation between buyer and seller whereby the seller's first counter-bid (i.e., the seller's first counteroffer) would consistently exceed her reservation value. This is consistent with the theoretical model in Merlo et al. (2015), but rather than the list price, it is the first counter-bid of the seller that acts as a "starting point" for the subsequent

[31]The lower bound measure (denoted by LB in the table) is consistently below the upper bound and model-generated mean log valuation, which is consistent with the way the two measures are constructed. In terms of standard deviations, the LB and UB measures are quite similar apart from two of the small apartment segments (in the years 2010 and 2012), where the standard deviation of the LB measure is around 2 times larger, which likely reflect substantial outliers in terms of very low initial bids.

Table 6: Non-targeted model moments for log valuations of auction losers.

#	Type	Year	Mean			Std. dev.		
			Model	Data		Model	Data	
				LB	UB		LB	UB
1	Small apt.	2010	6.022	5.958	5.951	0.305	0.753	0.331
2	Small apt.	2011	6.086	5.989	6.004	0.321	0.324	0.321
3	Small apt.	2012	6.180	6.049	6.056	0.307	0.589	0.321
4	Small apt.	2013	6.165	6.078	6.090	0.299	0.312	0.301
5	Small apt.	2014	6.150	6.083	6.095	0.308	0.314	0.307
6	Small apt.	2015	6.276	6.191	6.206	0.295	0.299	0.295
7	Large apt.	2010	6.133	6.137	6.152	0.396	0.415	0.412
8	Large apt.	2011	6.284	6.251	6.265	0.404	0.441	0.440
9	Large apt.	2012	6.349	6.209	6.223	0.411	0.451	0.447
10	Large apt.	2013	6.306	6.273	6.293	0.390	0.415	0.412
11	Large apt.	2014	6.298	6.276	6.290	0.415	0.416	0.413
12	Large apt.	2015	6.470	6.453	6.463	0.446	0.476	0.471
13	House	2010	6.646	6.644	6.660	0.290	0.278	0.276
14	House	2011	6.655	6.723	6.731	0.311	0.334	0.300
15	House	2012	6.747	6.761	6.773	0.308	0.300	0.298
16	House	2013	6.808	6.798	6.808	0.293	0.293	0.290
17	House	2014	6.771	6.832	6.841	0.304	0.313	0.301
18	House	2015	6.850	6.925	6.938	0.305	0.310	0.307

Note: The model-generated mean of (standard deviation of) log valuation is given by the conditional expectation (standard deviation) of $\log \tilde{v}(\theta, u_i)$, conditional on sale, $\tilde{B} > 1$, $u_i < \boldsymbol{u}_{(\tilde{B})}$, and $u_i \geq \hat{u}$. The data-generated moments are based on the highest bid that a losing bidder submits in the bidding log (LB), and on the bid that is submitted by another bidder subsequent to the bidder's highest bid (UB) for objects sold in the first attempt as defined in Section 4.1.

negotiations.

Table 7: Non-targeted model moments for log seller reservation values.

			Mean		Std. dev.	
#	Type	Year	Model	Data	Model	Data
1	Small apt.	2010	5.948	5.983	0.306	0.288
2	Small apt.	2011	6.008	6.079	0.321	0.287
3	Small apt.	2012	6.104	6.172	0.307	0.279
4	Small apt.	2013	6.092	6.190	0.299	0.257
5	Small apt.	2014	6.064	6.231	0.307	0.324
6	Small apt.	2015	6.189	6.372	0.293	0.314
7	Large apt.	2010	6.036	6.223	0.397	0.406
8	Large apt.	2011	6.187	6.244	0.405	0.340
9	Large apt.	2012	6.249	6.306	0.412	0.363
10	Large apt.	2013	6.211	6.396	0.390	0.421
11	Large apt.	2014	6.186	6.383	0.412	0.421
12	Large apt.	2015	6.341	6.520	0.444	0.464
13	House	2010	6.599	6.716	0.287	0.301
14	House	2011	6.606	6.696	0.308	0.318
15	House	2012	6.696	6.799	0.304	0.301
16	House	2013	6.759	6.827	0.290	0.338
17	House	2014	6.710	6.772	0.299	0.308
18	House	2015	6.781	6.960	0.300	0.296

Note: The model-generated mean (standard deviation) of the seller's reservation value is given by the conditional expectation (standard deviation) of $\log \tilde{v}(\theta, e)$, conditional on sale and either (i) a situation with entry of only one bidder (i.e. $\tilde{B} = 1$) or (ii) a situation with multiple bidder entry ($\tilde{B} > 1$), where at most one bidder has a valuation above the seller reservation value. The data-generated moments are based on the first counterbid a seller makes for objects where the seller makes a counterbid and which are sold in the first attempt as defined in Section 4.1.

6 Counterfactual exercises

Next, we use the estimated model in a number of counterfactual exercises. First, we assess the contribution of quality towards prices and price dispersion. Next, we assess the contribution of match quality via idiosyncratic buyer tastes or the frictional entry into bidding of potential buyers for prices and residual price dispersion. We also examine the importance of seller-specific preferences, as well as the informational frictions (the list price wedge). Third, we assess the effect of number of bidders on house prices in our model, and compare them against estimates from other studies.

6.1 Effects of quality

Table 8 shows the average log price and the standard deviation of log price by type of housing based on data from the estimated model, together with the average and standard

Table 8: Contribution of quality θ to mean and standard deviation of log sale prices.

	Small apt.	Large apt.	House
$E[\log p]$	6.1370	6.2877	6.7614
$E[\log p - \theta]$	0.0472	0.0420	0.0769
$SD(\log p)$	0.3086	0.4140	0.3032
$SD(\log p - \theta)$	0.0452	0.0432	0.0509
$Var(\log p - \theta)/Var(\log p)$	2.145 %	1.088 %	2.819 %

Note: The table reports the mean and standard deviation of log price and log price minus θ in the estimated model for the three different types of housing, as well as the ratio of the variance of log price minus theta over the variance of log price. Small apartments have up to 2 rooms, while large apartments have 3 or more rooms. Houses are defined as all remaining housing units, which consist of row and semi-detached houses, and single-family homes.

deviation of log price net of the common quality component θ. Several things stand out in this table. First, quality is the main driver of the average price and price dispersion according to the estimated model. This is not surprising, as attributes, such as size and location are the main drivers of house prices in essentially all pricing models used in research and by practitioners. More interestingly, the unexplained variation from fully accounting for quality differences is much lower than that implied by R^2 statistics from typical hedonic regressions. Using the last row from the table to compute an implied R^2, one obtains values in the range of 97 to 99 percent. In contrast, the typical hedonic regression tends to have an R^2 of around 80 to 90 percent. Table 9 reports R^2 from such a typical model (Model 1 in that table). In contrast, models that regress the log sale price on log list price (Model 2 in the table) or the appraisal value (Model 3 in the table) produce much higher values of R^2 – in line with the implied R^2 from Table 8.

Therefore, when *fully* accounted for, quality explains most of the variation in sale prices and to a similar extent as regressions that include the list price or appraisal values (which also fully account for quality, albeit with some noise). Put differently, estimating a typical hedonic model leaves substantial unexplained variation due to *unobservable* quality differences. Still, even after fully accounting for quality there remains a sizable "residual" price component that is driven by buyer/seller preference heterogeneity and frictions.[32]

6.2 Effects of preference heterogeneity and frictions

Next, we examine the importance of buyer and seller preference heterogeneity, as well as the transaction and informational frictions for prices and price dispersion. Following the discussion from the previous section, we focus on the "residualized" (log) price after removing the direct effects of quality on price. Therefore, we examine the object $\log \tilde{p} = \log p - \theta$. Table 10 shows how the mean and standard deviation of the "residualized" price

[32]Note that quality may still impact that residual price component indirectly due to selection effects.

Table 9: Adjusted R^2 for hedonic regression models.

	Model 1		Model 2		Model 3	
Type of unit	R^2	Obs.	R^2	Obs.	R^2	Obs.
Small apt.	0.846	5705	0.961	5952	0.959	3162
Large apt.	0.878	1616	0.969	1738	0.968	944
House	0.795	2044	0.932	2123	0.930	991

Note: The table reports the adjusted R^2 for 3 regression models with log of sale price as dependent variable. Model 1 is a standard hedonic regressions with log size, log size squared, indicator for lot size greater than 1000 square meters (for houses), log of common debt, year-by-month fixed effects, postal code fixed effects, and indicators for four construction periods. Model 2 has log of list price and log of common debt as regressors. Model 3 has log of appraised value and log of common debt as regressors. Each model is estimated for a specific type of unit in Oslo for the period 2010-2015. Small apartments have up to 2 rooms, while large apartments have 3 or more rooms. Houses are defined as all remaining housing units, which consist of row and semi-detached houses, and single-family homes.

Table 10: Counterfactual effects on the "residualized" price, $\log \tilde{p}$. Model extension.

(a) Mean

Counterfactual	Small apt.	Large apt.	Houses	Note
Baseline	0.0472	0.0420	0.0769	Baseline mean
$\sigma_u \to 0$	−130.29%	−136.82%	−110.32%	No dispersion in buyer tastes
$c \to 0$	9.09%	12.12%	4.13%	No bidding cost
$\sigma_e \to 0$	6.68%	9.27%	3.67%	No dispersion in seller preferences
$\sigma_\eta \to 0$	1.87%	2.59%	2.99%	Symmetric information
$\bar{e} = 0$	−2.66%	−3.06%	−18.72%	Mean zero seller reservation value

(b) Standard deviation

Counterfactual	Small apt.	Large apt.	Houses	Note
Baseline	0.0452	0.0432	0.0509	Baseline std. dev.
$\sigma_u \to 0$	−58.01%	−53.52%	−84.70%	No dispersion in buyer tastes
$c \to 0$	−14.68%	−17.61%	−11.74%	No bidding cost
$\sigma_e \to 0$	−20.82%	−24.88%	−14.61%	No dispersion in seller preferences
$\sigma_\eta \to 0$	−2.61%	−3.04%	−8.25%	Symmetric information
$\bar{e} = 0$	1.71%	1.81%	20.88%	Mean zero seller reservation value

Note: The table shows the percent change of mean (top panel) and the standard deviation (bottom panel) of log sale price less θ given the parameter estimates in Table 3, when changing parameters as indicated by the first column. The first row of the top panel shows the mean "residualized" price (in log points) at the parameter estimates. The first row of the bottom panel shows the standard deviation of the "residualized" price (in log points) at the parameter estimates.

changes for the different housing type segments in a number of counterfactual exercises.

To assess the contribution of match quality to the mean and standard deviation of the price premium, we perform two exercises. First, we directly reduce the idiosyncratic dispersion in buyer tastes, σ_u, to (close to) zero (Row 2 in Table 10). Therefore, this counterfactual exercise removes any differences in buyer preferences, and hence match quality aspects from the model, which also implies that any frictions associated with a finite number of potential buyers or informational mismatch become irrelevant for match quality. In this case, the average premium is fully reduced for all housing types, while the standard deviation goes down by between 55 and 85 percent, which translates into a reduction of between 0.025 to 0.04 log points. In our second exercise, we keep buyer taste dispersion fixed but rather decrease the bidding cost to near zero (Row 3). This counterfactual exercise illustrates the effect of a reduction in (search) frictions associated with the arrival of potential buyers. It should, therefore, imply a decrease in price dispersion, as the highest valuation buyers end up paying a price close to their valuation, which also implies a corresponding increase in the average sale price. Quantitatively, these effects are somewhat limited, however, which is due to selection effects as lower bidding costs imply the entry of lower valaution buyers, ceteris paribus, which has only a limited impact on the prices paid by the highest valuation buyer.

Turning to the contribution of the dispersion in seller-specific preferences (Rows 4) we observe a small effect on the average price and a slightly more sizable effect for price dispersion, which is around 1/5 to 1/3 of the effect of buyer taste heterogeneity. The list price wedge dispersion, σ_η (Row 5), has a fairly limited effect on both the mean and standard deviation of prices, suggesting a fairly limited quantitative role of informational mismatch at the estimated parameters. Finally, lowering the mean seller-specific preference (Row 6) has a substantial effect on the average "residualized" price only for houses where this mean value was estimated to be relatively large in magnitude. Here the main channel is selection effects as a lower mean seller-specific preference increases the sale of lower quality objects which both lower the average price and increase the price dispersion.

Overall, these exercises point to match quality being the main driver of "residualized" house price dispersion with match quality accounting for between 2.5 and 4 percentage points towards the observed house price dispersion in Oslo during 2010–2015. Moreover, buyer taste heterogeneity is also important for the observed average price *level* and contributed to around 5 to 7 percent higher house prices Oslo during 2010-2015.

6.3 Effects of number of bidders on prices

Using our estimated model for each sub-market, we generate simulated sales data and estimate the following regression

$$\log P_h = \alpha + \beta_1 \tilde{B}_h \left(+\beta_2 \theta_h\right) + \varepsilon_h, \tag{17}$$

in which $\tilde{B}$ denotes the number of bidders for property h. Therefore, we examine the effect of number of bidders on the final sale price using a reduced-form regression that is often estimated in the literature. Table 11 shows the coefficient estimates for the different segments. After fully controlling for quality, the effect of one more bidder on log prices is slightly less than 0.01. If instead we do not control for quality, we obtain twice as large coefficient estimates. Therefore, the coefficient estimates with and without controlling for quality provide bounds on the estimated effect of number of bidders on prices in reduced-form regressions, depending on how successfully one can control for housing quality. Interestingly, the coefficient estimates after controlling for quality are close to estimates reported in other empirical studies. For example, Genesove and Han (2016) estimate a reduced-form coefficient of bidders on log prices of 0.011 for a North American housing market, while Hungria-Gunnelin (2013) estimates a coefficient of around 0.04 using data for Stockholm, Sweden. Finally, Anundsen et al. (2022b) estimate an effect of between 0.02 and 0.03 for Norway. This provides another validation for our estimated model.

Table 11: Counterfactual effect of number of bidders on sale prices.

Housing type	$\tilde{B}$	$\tilde{B} \mid \theta$
Small apt.	0.0123	0.0064
Large apt.	0.0139	0.0062
House	0.0087	0.0056

Note: The table shows the estimated coefficients of the regression $\log P_h = \alpha + \beta_1 \tilde{B}_h + \beta_2 \theta_h + \varepsilon_h$, with (first column) and without (second column) controlling for quality, θ, in the regression.

7 Model extension

In this section, we extend our model by allowing for bidder valuations, and by implication house prices, to be directly influenced by the number of buyers bidding for a property. This channel serves as a counterpoint to the effect of match quality, as it can also increase residual price dispersion. It is also an interesting channel for generating house price dispersion in and of itself given anecdotal evidence of bidders in the housing market "overbidding" when engaging in a bidding war with multiple other bidders.

There are multiple possible channels for why bidder valuations might be increasing in the number of other bidders. For example, if buyers are risk-averse and uncertain about the common quality θ, then a larger number of bidders may end up decreasing their *ex post* uncertainty about θ and increase their willingness-to-pay. Alternatively, there could be behavioral biases that lead to bidders increasing their bids when they bid against more bidders. For example, bidders may get locked into trying to win an auction even though they end up "overbidding" for a property, relative to what they are willing to pay without additional bidders (Malmendier and Lee (2011), Lacetera et al. (2016), Gargano and Giacoletti (2020)). Alternatively, bidders may engage in behavioral herding (Simonsohn and Ariely, 2008). We refer to these various channels as an "overbidding effect".

To incorporate this overbidding effect, we modify the buyer's valuation as follows,

$$w(\theta, u_i, B) = \exp\{\theta + u_i + \Delta B\} = \tilde{v}(\theta, u_i)\exp\{\Delta B\}, \tag{18}$$

in which θ and u_i are as in Section 3, while $\Delta \geq 0$ is the marginal overbidding effect, and B is the number of other buyers entering bidding.[33]

The modified buyer valuation also implies a different pricing function. Specifically, we modify Eq. (9) to be:[34]

$$p\left(\theta, \boldsymbol{u}, e, \tilde{B}\right) = \begin{cases} w(\theta, e, 0) & , \ \tilde{B} = 1 \\ w\left(\theta, \max\left\{\boldsymbol{u}_{(B)}, e\right\}, \tilde{B} - 1\right) & , \ \tilde{B} > 1 \end{cases}, \tag{19}$$

where $\boldsymbol{u}_{(B)}$ is the second (largest) order statistic of $\boldsymbol{u}$. Given this pricing function, one can easily show that the expected payoff of an entering bidder when $B \geq 1$ in Eq. (12) is scaled by $\exp\{\Delta B\}$ in the extended model. Consequently, entry is still given by Eq. (15), i.e. a marginal entrant still derives a positive expected payoff only when there is a negotiated sale, and so the equilibrium characterization from Proposition 1 also follows.

We estimate the modified model by including an additional moment for each year in our sample, which is informative about Δ. Specifically, we use the regression coefficient from a bivariate regression of the price premium ($\log p - \log a$) on the number of bid-

[33]When allowing for an overbidding effect, there are in principle two buyer valuations, a pre-entry valuation and a post-entry valuation. If buyers are naïve, they will not anticipate a change in their valuations post entry. In our extension we modify the buyer's post-entry valuation. However, we assume that buyers are not naïve and anticipate this change in valuations. This assumption is without loss of generality for the entry decision as that decision only depends on the expected payoff of a marginal bidder, which in turn depends on the probability that there is no entry of other bidders. In that event, there is also no overbidding effect.

[34]Strictly speaking, in the presence of informational mismatch and an overbidding effect, the price with more than one bidders is $p\left(\theta, \boldsymbol{u}, e, \tilde{B}\right) = \max w\left(\theta, \boldsymbol{u}_{(B)}, \tilde{B} - 1\right), w(\theta, e, 0)$. Nevertheless, we impose Eq. (19) as the pricing function in our extended model, since it drastically simplifies the numerical simulations. Whenever, informational mismatch is relatively limited, as is the case for our baseline model, this modification of the pricing function should have only second-order effects on the parameter estimates.

Table 12: Parameter estimates. Model extension.

	Small apt.	Large apt.	House
σ_u	0.0171 (0.0081)	0.0144 (0.0157)	0.0239 (0.0108)
σ_e	0.0194 (0.0082)	0.0159 (0.0155)	0.0207 (0.0122)
σ_η	0.0066 (0.0074)	0.0305 (0.0130)	0.0135 (0.0111)
$\bar{e}$	0.0034 (0.0070)	0.0039 (0.0118)	0.0171 (0.0095)
$\bar{\eta}$	-0.0011 (0.0072)	-0.0035 (0.0135)	-0.0021 (0.0101)
c	2.6165 (0.0063)	0.7735 (0.0110)	8.5531 (0.0095)
Δ	0.0138 (0.0004)	0.0096 (0.0021)	0.0129 (0.0008)

Note: Standard errors in parenthesis. σ_u, σ_e, σ_η, $\bar{e}$, $\bar{\eta}$, and c are constrained to vary only by housing type, while remaining parameters may vary between years.

Table 13: Counterfactual effects on the "residualized" price, $\log \tilde{p}$. Model extension.

(a) Mean

Counterfactual	Small apt.	Large apt.	Houses	Note
Baseline	0.0541	0.0323	0.0763	Baseline mean premium
$\sigma_u \to 0$	-21.51%	-87.14%	16.93%	No dispersion in buyer tastes
$c \to 0$	41.53%	53.15%	25.39%	No bidding cost
$\sigma_e \to 0$	70.67%	109.39%	49.23%	No dispersion in seller preferences
$\sigma_\eta \to 0$	27.39%	67.14%	33.25%	Symmetric information
$\bar{e} = 0$	-9.69%	-2.35%	-38.15%	Mean zero seller reservation value
$\Delta = 0$	-57.69%	-37.11%	-47.89%	No overbidding effect

(b) Standard deviation

Counterfactual	Small apt.	Large apt.	Houses	Note
Baseline	0.0624	0.0277	0.0727	Baseline std. dev. of premium
$\sigma_u \to 0$	3.78%	-45.09%	-6.05%	No dispersion in buyer tastes
$c \to 0$	-7.28%	13.20%	-10.60%	No bidding cost
$\sigma_e \to 0$	19.43%	92.92%	10.54%	No dispersion in seller preferences
$\sigma_\eta \to 0$	13.80%	78.01%	12.29%	Symmetric information
$\bar{e} = 0$	-4.17%	3.67%	-20.01%	Mean zero seller reservation value
$\Delta = 0$	-59.01%	-32.51%	-58.12%	No overbidding effect

Note: The table shows the percent change of mean (top panel) and the standard deviation (bottom panel) of log sale price less θ given the model extension with parameter estimates as in Table 12, when changing parameters as indicated by the first column. The first row of the top panel shows the mean "residualized" price (in log points) at the parameter estimates. The first row of the bottom panel shows the standard deviation of the "residualized" price (in log points) at the parameter estimates.

ders. Table 12 reports the estimated parameters for our extended model.[35] Overall, the remaining parameter estimates are similar to those in our baseline model (cf. Table A.3) except the dispersion in buyer idiosyncratic tastes which is consistently lower for all types of housing. The estimated value of Δ is around 0.01, implying that bidder valuations and house prices increase with around 1 percent for every additional bidder that enters.

Turning to the counterfactual effects of preference heterogeneity and the frictions on the "residualized" price dispersion (Table 13), the contribution of buyer preference heterogeneity is notably lower for small apartments and houses.[36] In terms of the overbidding effect, setting $\Delta = 0$, we uncover a sizable effect that is comparable to the effect for both the average price and price dispersion. Interestingly, with an overbidding effect, the dispersion in seller-specific preferences and the list price wedge matters a lot more for house prices and price dispersion. The reason is that the overbidding effect acts to propagate and amplify variation in list prices in the final sale price. Since seller-specific preferences and the dispersion in the list price wedge impact the list price, they now matter much more for final sale prices as well.

Therefore, our extended model suggests that the channels which we proxy with our overbidding effect can be important drivers of house price dispersion for some housing segments.

8 Conclusion

Using a unique auction-level data set for housing sales for Oslo, Norway, we estimate a structural model of the housing transaction process, which explicitly includes the (endogenously determined) possibility of negotiated versus auctioned sales. We find that quality matters substantially more for price dispersion than typical hedonic pricing models would suggest, pointing to the importance of unobserved heterogeneity in the housing market. Beyond quality, buyer taste heterogeneity matters the most for any residual price dispersion, with the distribution of seller-specific preferences having a smaller impact on price dispersion. Finally, there is a partial disconnect between list prices and seller reservation values, which implies that buyers face imperfect information about seller reservation values when making bidding decisions, leading to informational mismatch.

One important insight from our analysis is that match quality matters not just for price dispersion but for average house prices as well. However, the relative importance of match quality for house prices versus price dispersion depends on the underlying frictions that potential buyers face. Lower entry of potential buyers leads to a lower average price,

[35] See Table A.5 in the Appendix includes the estimated parameters for the distribution of θ, while Table A.6 in the Appendix shows the simulated and data moments for all segments for the extended model.

[36] The effects of quality on the mean and standard deviation of log sale prices is similar to that in the baseline model, though the residual price variation is slightly lower – see Table A.7.

but also to higher price dispersion. Therefore, any policy that tries to "cool down" the housing market by reducing bidder entry via either macro-prudential tools (for example, as analyzed in DeFusco et al. (2020) or Han et al. (2021))) or direct regulation of the housing market transaction process (Chi et al., 2021) would have the unintended effect of increasing price dispersion and subjecting home owners to greater uninsurable housing wealth risk, which may have spillover effects on their spending decisions. We find these issues to be important for future research on this topic.

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Match Quality and House Price Dispersion: Evidence from Norwegian Housing Auctions

Online Appendix

André K. Anundsen Arne Lyshol Plamen T. Nenov Erling Røed Larsen

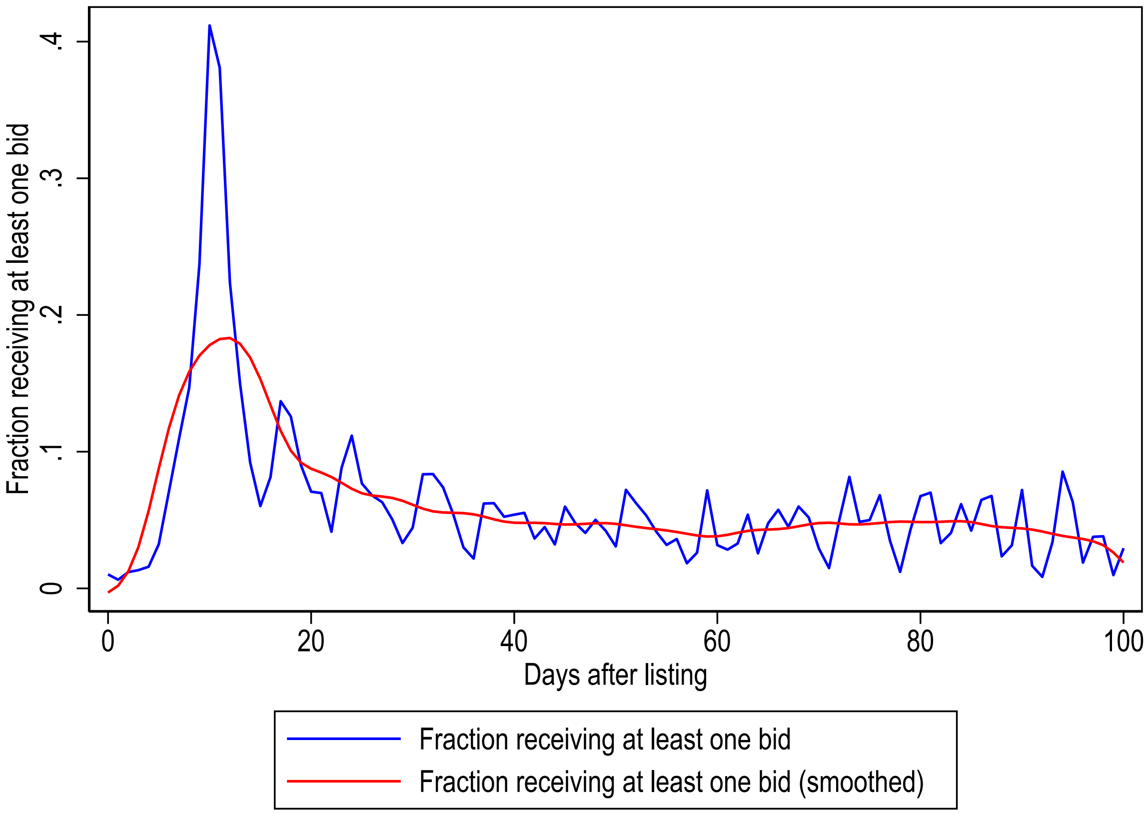
A Additional results

Table A.1: Data trimming

Step:	Both firms		Krogsveen		DNB	
	Bids	Trans.	Bids	Trans.	Bids	Trans
Initial data set (excl. Coops)	60,217	6,003	73,007	8,031	133,224	14,034
Drop missing sell, ask, size	59,932	5,928	72,289	7,742	132,221	13,670
Truncate on 1^{st} and 99^{th} pct. of size, ask, sell	57,479	5,678	69,170	7,410	126,649	13,088
Drop all transactions of units with more than three sales	57,225	5,646	68,800	7,368	126,025	13,014
Drop if TOM < 0	57,150	5,630	68,800	7,368	125,950	12,998
Drop missing bids or if bid $<$ 80% of list price†	54,586	5,629	66,534	7,368	121,120	12,997
Additional constraints (see tablenotes)	50,621	5,122	63,188	6,922	113,809	12,044

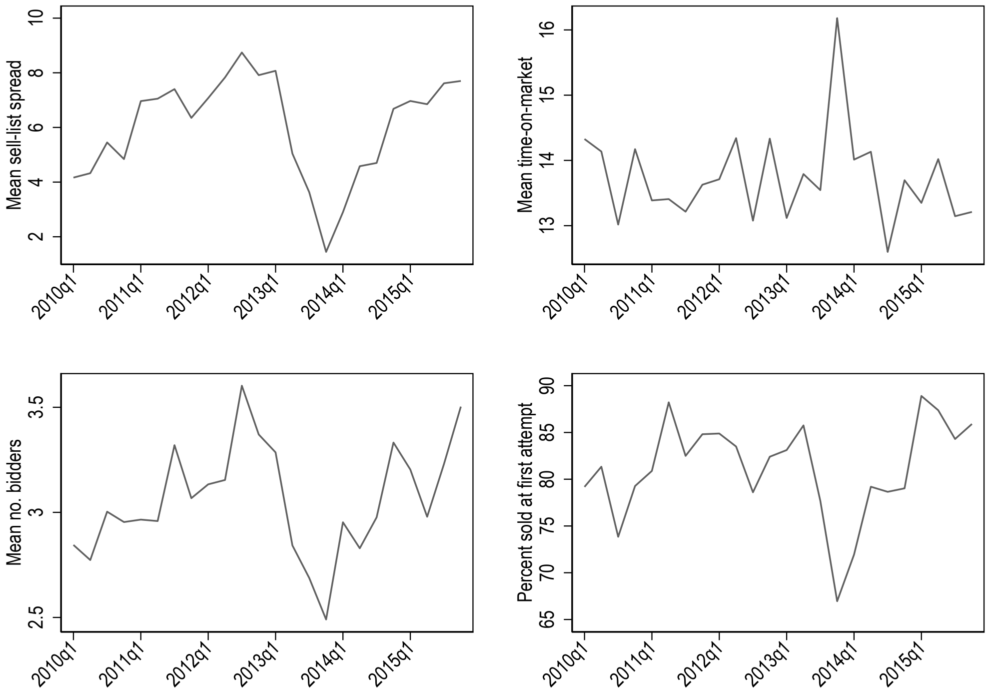
Note: The table shows the different steps taken when trimming the data. We show the number of bids and transactions after each step, both for the full sample of both firms, as well as for the individual firms. †: We do not drop bids lower than 80% of the list price if it is the winning bid. The additional constraints are: We drop the entire auction (all bids) if one bid is missing expiration date and there are less than 5 bidders, or if more than one bid is missing the expiration date of the bid. In addition, we drop only the bid with missing expiration date if there are more than 5 bidders and only one bid has missing expiration date. We drop the entire auction if the bid expires before it is received and there are less than 5 bidders, or if more than one bid expires before it is received. In addition, we drop only the bid that expires before it is received if there are more than 5 bidders and only one bid expires before it is received. We drop the entire auction if the distance (in days) between expiration of the previous bid and receiving a new bid is very long (99.5th pct) or short (0.5th pct) and there are less than 5 bidders, or if more than one bid has a long/short distance (in days) between expiration of the previous bid and receiving a new bid. In addition, we drop only the bid that has a long/short distance (in days) between expiration of the previous bid and receiving a new bid if there are more than 5 bidders and only one bid has a long/short distance (in days) between expiration of the previous bid and receiving a new bid. Finally, we truncate on 1st and 99th pct of number of days elapsed between ready for sale date and date of hiring the realtor.

Figure A.1: Bidding hazard.



Note: The figure plots the estimated fraction of unsold properties that receive a bid in a given day against the number of days since the listing date for properties in Oslo sold by the realtor firm Krogsveen. The red line is LOESS-smoothed with a smoothing parameter of 0.2.

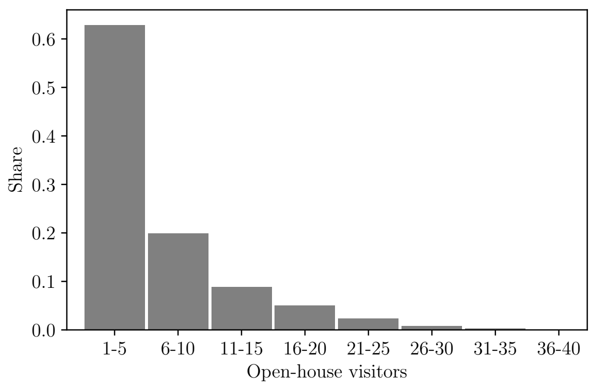
Figure A.2: Housing market developments in Oslo. 2010–2015.



Note: The upper left panel plots the mean sell-list spread, the upper right panel shows the mean time-on-market, the lower left panel displays mean number of bidders, whereas the lower right panel show the percentage number of units sold at the first sales attempt (within four weeks of the listing date). The time period is 2010–2015.

Figure A.3: Empirical distribution of open-house visitors.

(a) Small apartments, 2011



(b) Houses, 2014

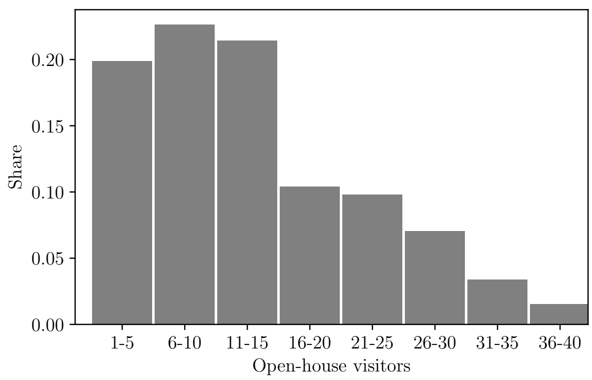


Table A.2: Parameter estimates (all parameters).

	Small apt.	Large apt.	House
σ_u	0.0350 (0.0081)	0.0315 (0.0160)	0.0465 (0.0106)
σ_e	0.0339 (0.0080)	0.0353 (0.0157)	0.0232 (0.0122)
σ_η	0.0109 (0.0073)	0.0121 (0.0130)	0.0261 (0.0111)
$\bar{e}$	0.0030 (0.0070)	0.0031 (0.0119)	0.0289 (0.0094)
$\bar{\eta}$	-0.0012 (0.0072)	-0.0009 (0.0134)	-0.0010 (0.0100)
c	2.5804 (0.0061)	3.3942 (0.0111)	8.7316 (0.0095)
$\sigma_{\theta,2010}$	0.3061 (0.0012)	0.4018 (0.0024)	0.2889 (0.0015)
$\sigma_{\theta,2011}$	0.3215 (0.0015)	0.4093 (0.0023)	0.3097 (0.0018)
$\sigma_{\theta,2012}$	0.3064 (0.0015)	0.4160 (0.0030)	0.3063 (0.0029)
$\sigma_{\theta,2013}$	0.2987 (0.0124)	0.3935 (0.0286)	0.2913 (0.0161)
$\sigma_{\theta,2014}$	0.3067 (0.0116)	0.4158 (0.0296)	0.3010 (0.0168)
$\sigma_{\theta,2015}$	0.2929 (0.0100)	0.4474 (0.0265)	0.3020 (0.0167)
$\bar{\theta}_{2010}$	5.9584 (0.0093)	6.0555 (0.0221)	6.5770 (0.0148)
$\bar{\theta}_{2011}$	6.0213 (0.0100)	6.2096 (0.0240)	6.5839 (0.0172)
$\bar{\theta}_{2012}$	6.1175 (0.0090)	6.2726 (0.0214)	6.6759 (0.0158)
$\bar{\theta}_{2013}$	6.1034 (0.0028)	6.2323 (0.0055)	6.7388 (0.0019)
$\bar{\theta}_{2014}$	6.0885 (0.0004)	6.2272 (0.0008)	6.7014 (0.0013)
$\bar{\theta}_{2015}$	6.2153 (0.3629)	6.3977 (0.7803)	6.7806 (1.3102)

Note: Standard errors in parenthesis. σ_u, σ_e, σ_η, $\bar{e}$, $\bar{\eta}$, and c are constrained to vary only by housing type, whilst remaining parameters may vary between years.

Table A.3: Targeted model moments and loss.

			$E[\log p]$		$E[p^*]$		$E[p^* \mid B=1]$		$CV(\log p)$		$CV(\log a)$		$Pr(sale)$		$Pr(sale \mid \tilde{B}>0)$		$Pr(\tilde{B} \geq 5)$		$Pr(p \leq a)$		
#	Type	Year	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Δ loss
1	Small apt.	2010	5.999	5.996	0.037	0.039	0.002	-0.004	0.051	0.051	0.051	0.051	0.787	0.789	0.911	0.930	0.050	0.122	0.218	0.242	0.0561
2	Small apt.	2011	6.067	6.074	0.041	0.070	0.002	0.014	0.053	0.053	0.053	0.054	0.806	0.856	0.920	0.949	0.076	0.190	0.200	0.129	0.1747
3	Small apt.	2012	6.164	6.151	0.044	0.080	0.002	0.017	0.050	0.049	0.050	0.053	0.820	0.860	0.925	0.955	0.086	0.217	0.189	0.109	0.2693
4	Small apt.	2013	6.148	6.146	0.042	0.046	0.002	0.000	0.049	0.048	0.049	0.050	0.814	0.797	0.922	0.921	0.077	0.140	0.194	0.236	0.0575
5	Small apt.	2014	6.156	6.159	0.062	0.044	0.002	0.002	0.051	0.051	0.050	0.053	0.889	0.796	0.963	0.926	0.197	0.180	0.125	0.202	0.1830
6	Small apt.	2015	6.288	6.295	0.069	0.072	0.002	0.019	0.047	0.048	0.047	0.052	0.915	0.895	0.973	0.966	0.232	0.217	0.104	0.131	0.1496
7	Large apt.	2010	6.104	6.100	0.036	0.039	0.002	-0.008	0.066	0.066	0.066	0.065	0.767	0.749	0.903	0.912	0.065	0.130	0.231	0.223	0.0617
8	Large apt.	2011	6.259	6.253	0.039	0.065	0.002	0.002	0.065	0.067	0.065	0.068	0.785	0.854	0.909	0.935	0.079	0.217	0.216	0.161	0.1764
9	Large apt.	2012	6.321	6.284	0.038	0.069	0.002	0.015	0.066	0.066	0.066	0.069	0.785	0.808	0.906	0.923	0.073	0.203	0.218	0.128	0.1773
10	Large apt.	2013	6.279	6.289	0.038	0.045	0.002	0.001	0.063	0.062	0.063	0.064	0.784	0.819	0.906	0.939	0.073	0.146	0.220	0.245	0.0807
11	Large apt.	2014	6.293	6.318	0.054	0.041	0.002	0.007	0.066	0.065	0.066	0.067	0.864	0.761	0.951	0.903	0.181	0.133	0.152	0.216	0.1563
12	Large apt.	2015	6.469	6.471	0.060	0.059	0.002	0.021	0.069	0.068	0.070	0.070	0.891	0.856	0.962	0.947	0.218	0.175	0.128	0.136	0.0767
13	House	2010	6.655	6.657	0.041	0.056	0.008	-0.007	0.044	0.044	0.044	0.044	0.749	0.803	0.927	0.950	0.118	0.221	0.250	0.235	0.0935
14	House	2011	6.660	6.665	0.038	0.053	0.008	0.005	0.047	0.047	0.047	0.046	0.730	0.811	0.918	0.957	0.098	0.144	0.265	0.200	0.1130
15	House	2012	6.752	6.757	0.039	0.057	0.008	0.007	0.046	0.046	0.046	0.046	0.747	0.753	0.923	0.915	0.109	0.177	0.255	0.190	0.0592
16	House	2013	6.817	6.814	0.043	0.041	0.008	-0.003	0.043	0.044	0.043	0.043	0.773	0.757	0.933	0.917	0.124	0.147	0.238	0.264	0.0164
17	House	2014	6.798	6.798	0.061	0.042	0.010	0.009	0.045	0.045	0.045	0.045	0.847	0.710	0.967	0.899	0.234	0.185	0.165	0.239	0.1545
18	House	2015	6.886	6.888	0.071	0.057	0.011	0.014	0.045	0.045	0.044	0.045	0.891	0.792	0.982	0.949	0.283	0.225	0.130	0.225	0.1206

Note: The table shows targeted moments in the baseline estimation for individual segments. $p^* = \log p - \log a$.

Table A.4: Parameter estimates with time-varying parameters.

#	Type	Year	σ_θ	θ	σ_u	σ_e	σ_η	$\bar{e}$	$\bar{\eta}$	c
1	Small apt.	2010	0.3079 (0.0191)	6.0003 (0.0322)	0.0000 (0.0007)	0.0292 (0.0195)	0.0033 (0.0180)	-0.04 (0.00)	0.01 (0.00)	1.02 (1.34)
2	Small apt.	2011	0.3211 (0.0081)	5.9943 (0.0138)	0.0614 (0.0049)	0.0112 (0.0017)	0.0308 (0.0046)	0.02 (0.00)	-0.01 (0.00)	0.74 (1.07)
3	Small apt.	2012	0.2940 (0.0075)	6.0773 (0.0127)	0.0516 (0.0048)	0.0094 (0.0021)	0.0376 (0.0044)	0.02 (0.00)	-0.02 (0.00)	0.06 (0.11)
4	Small apt.	2013	0.2974 (0.0070)	6.0766 (0.0103)	0.0520 (0.0029)	0.0234 (0.0033)	0.0176 (0.0057)	0.03 (0.00)	0.00 (0.00)	2.66 (1.34)
5	Small apt.	2014	0.3165 (0.0072)	6.1693 (0.0098)	0.0000 (0.0001)	0.0319 (0.0025)	0.0023 (0.0010)	-0.04 (0.00)	0.00 (0.00)	1.35 (0.17)
6	Small apt.	2015	0.2967 (0.0061)	6.2057 (0.0097)	0.0371 (0.0019)	0.0214 (0.0022)	0.0433 (0.0025)	0.03 (0.00)	-0.02 (0.00)	0.74 (0.25)
7	Large apt.	2010	0.4031 (0.0160)	6.0354 (0.0301)	0.0413 (0.0100)	0.0232 (0.0115)	0.0109 (0.0123)	0.02 (0.02)	0.00 (0.00)	3.00 (3.26)
8	Large apt.	2011	0.4182 (0.0159)	6.1637 (0.0305)	0.0675 (0.0056)	0.0159 (0.0066)	0.0139 (0.0140)	0.03 (0.01)	0.00 (0.00)	1.62 (4.80)
9	Large apt.	2012	0.4126 (0.0131)	6.2029 (0.0301)	0.0647 (0.0074)	0.0179 (0.0040)	0.0263 (0.0058)	0.03 (0.01)	-0.01 (0.00)	2.97 (4.10)
10	Large apt.	2013	0.3936 (0.0117)	6.2135 (0.0232)	0.0519 (0.0044)	0.0147 (0.0027)	0.0279 (0.0088)	0.03 (0.00)	0.00 (0.00)	1.64 (1.70)
11	Large apt.	2014	0.4157 (0.0653)	6.3127 (0.1055)	0.0000 (0.0023)	0.0303 (0.0153)	0.0018 (0.0044)	-0.04 (0.01)	0.00 (0.01)	1.80 (1.81)
12	Large apt.	2015	0.4420 (0.0240)	6.4771 (0.0239)	0.0000 (0.0001)	0.0326 (0.0026)	0.0002 (0.0013)	-0.05 (0.00)	0.00 (0.00)	1.10 (0.28)
13	House	2010	0.2887 (0.0107)	6.5562 (0.0177)	0.0629 (0.0054)	0.0156 (0.0040)	0.0273 (0.0149)	0.03 (0.01)	0.01 (0.00)	2.98 (3.84)
14	House	2011	0.3079 (0.0123)	6.5881 (0.0175)	0.0534 (0.0049)	0.0132 (0.0026)	0.0260 (0.0082)	0.02 (0.00)	-0.00 (0.00)	2.99 (2.39)
15	House	2012	0.3068 (0.0111)	6.6658 (0.0183)	0.0553 (0.0051)	0.0234 (0.0045)	0.0336 (0.0080)	0.04 (0.00)	-0.01 (0.00)	2.97 (2.20)
16	House	2013	0.2941 (0.0096)	6.7446 (0.0155)	0.0437 (0.0040)	0.0237 (0.0048)	0.0304 (0.0084)	0.03 (0.00)	0.00 (0.00)	2.98 (1.59)
17	House	2014	0.3121 (0.0135)	6.7668 (0.0265)	0.0000 (0.0005)	0.0119 (0.0144)	0.0415 (0.0114)	-0.01 (0.02)	-0.01 (0.01)	2.93 (3.57)
18	House	2015	0.3108 (0.0097)	6.8846 (0.0420)	0.0034 (0.0192)	0.0221 (0.0114)	0.0660 (0.0095)	-0.02 (0.07)	-0.02 (0.03)	0.31 (0.43)

Table A.5: Parameter estimates (all parameters). Model extension.

	Small apt.	Large apt.	House
σ_u	0.0171 (0.0081)	0.0144 (0.0157)	0.0239 (0.0108)
σ_e	0.0194 (0.0082)	0.0159 (0.0155)	0.0207 (0.0122)
σ_η	0.0066 (0.0074)	0.0305 (0.0130)	0.0135 (0.0111)
$\bar{e}$	0.0034 (0.0070)	0.0039 (0.0118)	0.0171 (0.0095)
$\bar{\eta}$	-0.0011 (0.0072)	-0.0035 (0.0135)	-0.0021 (0.0101)
c	2.6165 (0.0063)	0.7735 (0.0110)	8.5531 (0.0095)
Δ	0.0138 (0.0004)	0.0096 (0.0021)	0.0129 (0.0008)
$\sigma_{\theta,2010}$	0.2747 (0.0012)	0.4044 (0.0025)	0.2824 (0.0023)
$\sigma_{\theta,2011}$	0.3255 (0.0017)	0.4073 (0.0033)	0.3063 (0.0029)
$\sigma_{\theta,2012}$	0.2610 (0.0009)	0.4166 (0.0026)	0.3136 (0.0027)
$\sigma_{\theta,2013}$	0.2882 (0.0118)	0.3935 (0.0283)	0.2916 (0.0162)
$\sigma_{\theta,2014}$	0.2981 (0.0115)	0.4216 (0.0290)	0.3056 (0.0169)
$\sigma_{\theta,2015}$	0.2752 (0.0097)	0.4338 (0.0260)	0.2877 (0.0167)
$\bar{\theta}_{2010}$	5.9417 (0.0091)	6.0506 (0.0217)	6.5805 (0.0149)
$\bar{\theta}_{2011}$	6.0216 (0.0096)	6.2101 (0.0230)	6.5956 (0.0173)
$\bar{\theta}_{2012}$	6.0939 (0.0088)	6.2838 (0.0214)	6.6840 (0.0162)
$\bar{\theta}_{2013}$	6.0975 (0.0022)	6.2417 (0.0030)	6.7408 (0.0034)
$\bar{\theta}_{2014}$	6.0762 (0.0003)	6.2685 (0.0019)	6.6880 (0.0010)
$\bar{\theta}_{2015}$	6.1818 (0.3283)	6.4344 (0.2050)	6.7784 (1.8331)

Note: Standard errors in parenthesis. σ_u, σ_e, σ_η, $\bar{e}$, $\bar{\eta}$, and c are constrained to vary only by housing type, whilst remaining parameters may vary between years.

Table A.6: Targeted model moments and loss. Model extension.

#	Type	Year	$E[\log p]$		$E[p^*]$		$E[p^* \mid B=1]$		$CV(\log p)$		$CV(\log a)$		$Pr(sale)$		$Pr(sale \mid \tilde{B}>0)$		$Pr(\tilde{B} \geq 5)$		$Pr(p \leq a)$		Bidder coefficient		
			Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Δ loss
1	Small apt.	2010	5.987	5.996	0.034	0.039	0.002	-0.004	0.046	0.051	0.046	0.051	0.745	0.789	0.931	0.930	0.051	0.122	0.187	0.242	0.015	0.021	0.1496
2	Small apt.	2011	6.077	6.074	0.041	0.070	0.002	0.014	0.054	0.053	0.054	0.054	0.769	0.856	0.940	0.949	0.077	0.190	0.171	0.129	0.015	0.022	0.3171
3	Small apt.	2012	6.146	6.151	0.043	0.080	0.002	0.017	0.043	0.049	0.043	0.053	0.787	0.860	0.946	0.955	0.087	0.217	0.162	0.109	0.015	0.023	0.4589
4	Small apt.	2013	6.149	6.146	0.041	0.046	0.002	0.000	0.048	0.048	0.047	0.050	0.781	0.797	0.943	0.921	0.078	0.140	0.165	0.236	0.015	0.024	0.1935
5	Small apt.	2014	6.161	6.159	0.073	0.044	0.002	0.002	0.050	0.051	0.049	0.053	0.857	0.796	0.980	0.926	0.198	0.180	0.111	0.202	0.014	0.020	0.4396
6	Small apt.	2015	6.275	6.295	0.084	0.072	0.002	0.019	0.046	0.048	0.044	0.052	0.886	0.895	0.988	0.966	0.231	0.217	0.095	0.131	0.014	0.019	0.4557
7	Large apt.	2010	6.091	6.100	0.029	0.039	0.000	-0.008	0.066	0.066	0.066	0.065	0.785	0.749	0.914	0.912	0.006	0.130	0.251	0.223	0.024	0.023	0.1335
8	Large apt.	2011	6.251	6.253	0.031	0.065	-0.000	0.002	0.065	0.067	0.065	0.068	0.802	0.854	0.914	0.935	0.010	0.217	0.240	0.161	0.023	0.026	0.2949
9	Large apt.	2012	6.324	6.284	0.030	0.069	-0.000	0.015	0.066	0.066	0.066	0.069	0.803	0.808	0.910	0.923	0.009	0.203	0.241	0.128	0.023	0.025	0.2789
10	Large apt.	2013	6.281	6.289	0.030	0.045	-0.000	0.001	0.063	0.062	0.063	0.064	0.802	0.819	0.912	0.939	0.008	0.146	0.243	0.245	0.023	0.020	0.1660
11	Large apt.	2014	6.320	6.318	0.042	0.041	-0.001	0.007	0.067	0.065	0.067	0.067	0.880	0.761	0.963	0.903	0.026	0.133	0.182	0.216	0.022	0.024	0.2508
12	Large apt.	2015	6.490	6.471	0.046	0.059	-0.001	0.021	0.067	0.068	0.067	0.070	0.905	0.856	0.972	0.947	0.040	0.175	0.160	0.136	0.021	0.022	0.1958
13	House	2010	6.657	6.657	0.048	0.056	0.005	-0.007	0.043	0.044	0.042	0.044	0.704	0.803	0.925	0.950	0.122	0.221	0.171	0.235	0.013	0.024	0.2476
14	House	2011	6.671	6.665	0.045	0.053	0.005	0.005	0.046	0.047	0.046	0.046	0.685	0.811	0.913	0.957	0.102	0.144	0.185	0.200	0.013	0.028	0.3181
15	House	2012	6.759	6.757	0.045	0.057	0.005	0.007	0.047	0.046	0.046	0.046	0.706	0.753	0.920	0.915	0.113	0.177	0.174	0.190	0.013	0.024	0.2060
16	House	2013	6.819	6.814	0.051	0.041	0.005	-0.003	0.044	0.044	0.043	0.043	0.734	0.757	0.933	0.917	0.129	0.147	0.159	0.264	0.013	0.023	0.1515
17	House	2014	6.795	6.798	0.079	0.042	0.006	0.009	0.046	0.045	0.045	0.045	0.806	0.710	0.971	0.899	0.241	0.185	0.111	0.239	0.013	0.024	0.4820
18	House	2015	6.899	6.888	0.096	0.057	0.006	0.014	0.044	0.045	0.042	0.045	0.854	0.792	0.987	0.949	0.291	0.225	0.088	0.225	0.013	0.022	0.3768

Note: The table shows targeted moments in the estimation of the extended model for individual segments. $p^* = \log p - \log a$.

Table A.7: Contribution of quality θ to mean and standard deviation of log sale prices. Model extension.

	Small apt.	Large apt.	House
$E[\log p]$	6.1323	6.2929	6.7670
$E[\log p - \theta]$	0.0541	0.0323	0.0763
$SD(\log p)$	0.2939	0.4127	0.3049
$SD(\log p - \theta)$	0.0624	0.0277	0.0727
$Var(\log p - \theta)/Var(\log p)$	4.512 %	0.451 %	5.681 %

Note: The table reports the mean and standard deviation of log price and log price minus θ in the model extension for the three different types of housing, as well as the ratio of the variance of log price minus theta over the variance of log price. Small apartments have up to 2 rooms, while large apartments have 3 or more rooms. Houses are defined as all remaining housing units, which consist of row and semi-detached houses, and single-family homes.

B Omitted proofs from model

Proof of Lemma 1

To show that W is increasing in θ, note that for $B = 0$,

$$W(0, \theta, e, u_i) = (w(\theta, u_i) - w(\theta, e)) = \exp\{\theta\} (\exp\{u_i\} - \exp\{e\}),$$

and similarly for $B > 0$,

$$W(B, \theta, e, u_i) = \exp\{\theta\} \Pr\left\{(\boldsymbol{u}_{-i})_{(B)} < u_i\right\} \times \\ \left\{\exp\{u_i\} - E\left[\exp\left\{\max\left\{(\boldsymbol{u}_{-i})_{(B)}, e\right\}\right\} \middle| (\boldsymbol{u}_{-i})_{(B)} < u_i\right]\right\}.$$

Direct inspection of these expressions immediately implies that W is increasing in θ.

To show that W is increasing in u_i and decreasing in e, note that this is trivial for $B = 0$. For $B > 0$, we rewrite W as

$$W(B, \theta, e, u_i) = \exp\{\theta\} \left[\Pr\left\{(\boldsymbol{u}_{-i})_{(B)} < u_i\right\} \exp\{u_i\} \right. \\ \left. - \Pr\left\{(\boldsymbol{u}_{-i})_{(B)} < e\right\} \exp\{e\} - \int_e^{u_i} \exp\{x\} \psi_B(x)\, dx\right],$$

where $\psi_B(x)$ denotes the probability density function of the largest order statistic of $(\boldsymbol{u}_{-i})$. Differentiating with respect to u_i, we get

$$\begin{aligned} \frac{\partial W}{\partial u_i} &= \exp\{\theta\} \left[\psi_B(u_i) \exp\{u_i\} + \Pr\left\{(\boldsymbol{u}_{-i})_{(B)} < u_i\right\} \exp\{u_i\} - \exp\{u_i\} \psi_B(u_i)\right] \\ &= \exp\{\theta\} \Pr\left\{(\boldsymbol{u}_{-i})_{(B)} < u_i\right\} \exp\{u_i\} > 0. \end{aligned}$$

Similarly, differentiating with respect to e, we get

$$\begin{aligned}\frac{\partial W}{\partial e} &= \exp\{\theta\}\left[-\psi_B(e)\exp\{e\} - \Pr\left\{(\boldsymbol{u}_{-i})_{(B)} < e\right\}\exp\{e\} + \exp\{e\}\psi_B(e)\right] \\ &= -\exp\{\theta\}\Pr\left\{(\boldsymbol{u}_{-i})_{(B)} < e\right\}\exp\{e\} < 0.\end{aligned}$$

Finally, to show that W is decreasing in B, first of all note that

$$W(0,\theta,e,u_i) \geq W(1,\theta,e,u_i),$$

since $\Pr\left\{(\boldsymbol{u}_{-i})_{(B)} < u_i\right\} \leq 1$ and $E\left[\exp\left\{\max\left\{(\boldsymbol{u}_{-i})_{(B)}, e\right\}\right\}\middle|(\boldsymbol{u}_{-i})_{(B)} < u_i\right] \geq \exp\{e\}$.

For $B > 1$, note first that

$$\Pr\left\{(\boldsymbol{u}_{-i})_{(B)} < u_i\right\} = \Psi(u_i)^B$$

is decreasing in B, where $\Psi(x)$ is the cumulative distribution function of a Type 1 extreme value distribution, so $\Pr\left\{u_{(B)} < u_i\right\}$ is decreasing in B. Second, note that

$$\begin{aligned}(\boldsymbol{u}_{-i})_{(B)} &= \max\{u_1, u_2, u_3, ..., u_{i-1}, u_{i+1}, ..., u_{B-1}, u_B\} \geq \\ &\max\{u_1, u_2, u_3, ..., u_{i-1}, u_{i+1}, ..., u_{B-1}\} = (\boldsymbol{u}_{-i})_{(B-1)},\end{aligned}$$

and so

$$\exp\left\{\max\left\{(\boldsymbol{u}_{-i})_{(B)}, e\right\}\right\} \geq \exp\left\{\max\left\{(\boldsymbol{u}_{-i})_{(B-1)}, e\right\}\right\}.$$

These two observations directly imply that

$$W(B-1,\theta,u_i) \geq W(B,\theta,u_i),$$

for $B > 1$.

C Details on the estimation

Simulated method of moments

We describe in more detail the estimation procedure for the extension of the model, where all parameters are estimated year-by-year. We largely follow Hennessy and Whited (2007). For each segment, $j \in J$, we estimate the parameters, $\Phi_j = \{\sigma_u, \sigma_e, \sigma_\eta, \sigma_\theta, \bar{e}, \bar{\eta}, c, \bar{\theta}\}$, that satisfy

$$\bar{\Phi}_j = \underset{\Phi}{arg\,min}\, \bar{m}_K(X_j, \Phi) W_N^j \bar{m}_K(X_j, \Phi), \tag{C.1}$$

where W_N^j is a weighting matrix. We set it to the inverse of the covariance matrix of the data moments, V^j. The empirical variance-covariance matrix is computed by bootstrap separately for each segment. Specifically, for each segment, we use a non-parametric bootstrap to compute the covariance matrix. The bootstrap is done using 1,000 draws, with replacement. Also,

$$\bar{m}_K(X_j, \Phi) = \frac{1}{K} \sum_{k=1}^{K} m_k(X_j, \Phi), \tag{C.2}$$

where $m_k(X_j, \Phi) = m_n^d(X_j) - m_n^s(\Phi)$, a vector of empirical moments less their simulated counterparts. Each $m_k(X_j, \Phi)$ is computed from n simulated houses, equal to the number of houses sold in that segment. This number is typically too low for computational purposes. Therefore, the simulation is repeated K times for the same Φ. The moment used to compute the loss, $\bar{m}_K(X_j, \Phi)$, is the average moment of the K runs.

The model variance-covariance matrix is computed from

$$\left(1 + \frac{1}{K}\right) \left(J^T W_N^j J\right)^{-1} J^T W_N^j J \left(J^T W_N^j J\right)^{-1} \tag{C.3}$$

where J is the Jacobian matrix of $\bar{m}_K(X_j, \Phi)$ over Φ computed by central finite differences.[37]

For the baseline estimation, where some parameters are fixed across years within each housing type, we estimate the parameters as follows. For each group of segments, $g \in G$, we estimate the parameters, $\hat{\Phi}_g = \bigcup_{j \in g} \Phi_j$, that satisfy Equation (C.1) and specified time invariance constraints (e.g., $\sigma_u = \sigma_u^j \forall j \in G$). Now,

$$\bar{m}(X_g, \hat{\Phi}_g) = \text{vec}\left(\left\{\frac{1}{K_j} \sum_{k=1}^{K_j} m_{k_j}(X_j, \Phi_j)\right\}_{j \in g}\right) \tag{C.4}$$

with $m_{k_j}(\cdot)$ as before. The data variance-covariance matrix used for both the weighting matrix and for computing the model variance-covariance matrix is

$$V^g = \text{blockdiag}\left(\{V^j\}_{j \in g}\right) \tag{C.5}$$

where *blockdiag* generates a block diagonal matrix of its inputs. Note that since the off-block diagonal entries are zero, we are assuming that there is no correlation across years. The variance-covariance matrix is computed as in the baseline model.

[37] For parameters estimated close to or at range constraints, we compute the forward or backward finite difference.

Estimation algorithm

For each segment, with n sales, the parameters, Φ, are estimated as follows.

1. Make an initial guess for the parameters, $\Phi = \Phi_0$.

2. Initialise K datasets, with $K = \underset{k}{arg\,min}\{n \times K \geq N\}$. For each dataset,

   (a) Draw n of μ, θ, B_p, e, η.

   (b) Find the fixed-point of Eq. (15), $\hat{u}(\theta)$, with Brent's method.

   (c) For each house, draw B_p of u. Compute prices according to Eq. (9). Compute moments, $m_k(X_j, \Phi)$.

3. Average moments across the K datasets and compute $m_K(X_j, \Phi)$.

4. Compute loss function, $m_K(X_j, \Phi)W_N^j m_K(X_j, \Phi)$. According to the Nelder-Mead algorithm, evaluate the innovation in the loss function and, if required, updated the parameter guess, Φ, and repeat steps 2 through 4.[38]

[38]For some extensions we rely on the differential evolution algorithm due to Storn and Price (1997).