What is the Role of the Asking Price for a House?

Lu Han*
Rotman School of Management
105 St. George St.
University of Toronto
Toronto, ON M5S 3E6
Canada
lu.han@rotman.utoronto.ca
(416) 946-5294

William C. Strange
Rotman School of Management
105 St. George St.
University of Toronto
Toronto, ON M5S 3E6
Canada
wstrange@rotman.utoronto.ca
(416) 978-1949

October 23, 2012
Revised: March 6, 2016

*We thank the Social Sciences and Humanities Research Council of Canada for financial support. We are also grateful for the helpful comments we have received from Stuart Rosenthal, two anonymous referees, James Albrecht, Edward Glaeser, Jessie Hanbury, Edward Kung, Christopher Mayer, Shouyong Shi and participants in seminars at Cornell University, the University of Toronto, the NARSC Annual Meetings, the HULM conference, and NBER. We further thank Travis Chow and Yousuf Haque for very helpful work as research assistants.

Abstract

This paper considers the role of the asking price in housing transactions both theoretically and empirically. Significant fractions of housing transactions involve sales prices that are either below or above asking price, which might suggest that asking price has limited relevance. However, many housing transactions involve a sales price exactly equal to asking price (a fact that has previously drawn little notice), strongly suggesting that asking price does matter. The paper develops a model where asking price is neither a binding commitment nor a ceiling, yet still directs buyer search and impacts sales price. Using novel survey data, the paper provides empirical evidence consistent with asking price playing a directing role in buyer search. Consistent with theory, this effect is stronger for more atypical houses and in bust markets.

I. Introduction

When a house is put on the market, its seller lists an asking price. There are two reasons that this asking price is quite different from list prices for ordinary retail goods. First, buyers may be unwilling to pay the asking price, leading them to negotiate the price down. Although there are exceptions, this usually does not occur in retail markets with posted prices. Second, buyers may compete with each other with sufficient vigor that the sales price is pushed beyond the posted list price. Again, although there are exceptions, this also does not usually occur in posted price markets. It is tempting to conclude from this that a house's asking price is of limited relevance. Whether or not this is true is clearly of great importance. A house is typically the largest single asset in a household's portfolio, and housing as a whole is a significant fraction of aggregate wealth (Tracy and Schneider, 2001). The marketing of housing is thus highly significant to households and to the macro-economy.

This paper considers the role of the asking price in housing transactions both theoretically and empirically. It is motivated by three key stylized facts. First, as noted above, *a house's ultimate sales price is frequently below asking price*. Merlo and Ortalo-Magne (2004) find that the average ratio of sales price to asking price is 96% in a sample of UK sales from the mid-1990s. In US data from the National Association of Realtors, Han and Strange (2014) show that the ratio is also 96% for the same period. Not surprisingly, this means that a very significant fraction of sales are below the asking price (Case and Shiller, 1988 and 2003).[1] Liu et al (2014) show that this ratio is pro-cyclical using Phoenix data. Taken together, these descriptive statistics show that asking price is certainly not a posted price.

Second, in recent years, *sales price is frequently greater than asking price*. This was once rare. In Merlo and Ortalo-Magne's mid 1990s sample, only four percent of sales were at prices greater than the asking price. Han and Strange (2014) find a similar percentage at the same time in NAR data. Recent years, however, have seen more numerous bidding wars, where price is driven above asking price. The national share of above-list sales rose to around 15% during the 2000s boom. In some markets, the share rose to more than 30%. After the bust, this share fell, but at close to 10%, it remains much higher than its typical historical levels.[2] It is worth pointing out that the emergence of bidding wars did not simply replace the old negotiate-down approach. Even at the peak of the boom in 2005, the national average ratio of sales price to asking price was 98%, and the share of below-list sales was 54%. In this situation, the asking price is not a posted price. Neither is it a ceiling nor a floor.

---

[1]Case and Shiller (1988, 2003) report 1988 fractions of sales below list well above 50% for the cities of Boston, Los Angeles, Milwaukee, and San Francisco. While the fractions of below list sales are considerably smaller during the boom, their 2003 surveys continue to report significant fractions of sales at prices below list. Carrillo (2013) reports 73% of sales below asking price in a sample of Virginia house transactions.
[2]Case and Shiller (2003) also report growth in the fraction of sales above-list in the four cities that they survey.

Does this mean that the asking price has no impact on a house's sales price? One might suspect, given the frequency of above- and below-list sales, that housing transactions are simply some sort of auction, with the asking price a largely meaningless initiation to the process. In an English auction, price will be the realization of the second highest buyer valuation. In a Dutch auction, price will depend on the expectation of the second highest buyer valuation. In either case, with a continuous and atomless distribution generating the valuations, there is zero probability of asking price equaling sales price. The only role of asking price in this situation would be to "steer" buyers to particular market segments.

The third key stylized fact – one that has not previously been emphasized– contradicts this irrelevance result: *it is common for many housing sales to involve the acceptance of the asking price*. Case and Shiller (1998, 2003) report high levels of acceptance in both years of their survey. The four city average for 1988 was 27.9%. In 2003, it was 48.4%. They do not, however, comment on this phenomenon in the text of either paper. In a recent survey of homebuyers in a large North American metropolitan area (Genesove and Han, 2012b), one sees a lower share of purchases with sales price equal to asking price, but the fraction continues to be nontrivial, an average of 7.9%. That a finite share of buyers pay the asking price strongly suggests that asking price matters. But the question remains: why does it matter?

This paper's empirical work builds on a model of a home seller's problem where asking price plays an important role. It does so by acting as a ceiling only in some situations. The above discussion makes clear that a house is not like other goods in the sense that its posted price does not have the take-it-or-leave-it commitment force of a typical price posting. In fact, an asking price does have some meaningful commitment. Although there is not (to the best of our knowledge) a legal requirement in any jurisdiction that a seller must accept an offer equal to the asking price, the listing contract with a real estate agent creates a partial commitment of a similar nature by requiring the seller to pay the agent's commission if the seller rejects an unrestricted offer equal to or greater than the asking price. Furthermore, there may be behavioral reasons why a seller may feel committed to the asking price. So it is not unreasonable to believe that there is some commitment in the asking price.[3]

Most models of this commitment treat the asking price as a binding ceiling. In Chen and Rosenthal (1996a,b), the seller sets such a ceiling. Buyers make decisions of whether or not to incur the search costs associated with visiting a house and thus learning whether or not it is a good match. In the simplest version of the model, the seller makes a take-it-or-leave-it offer after the visit with knowledge of the buyer's match value. This allows the extraction of the entire surplus. The commitment to a ceiling price is a way that the seller can commit to limit such extraction, strengthening buyer search incentives. By setting a lower asking

[3] This explanation of why there is a mass point of sales prices is obviously very different than explanations of mass points in housing consumption that rely on a kinked budget constraint, as in Hoyt and Rosenthal's (1990, 1992) analysis of the impact of capital gains taxation on housing consumption.

price, the seller encourages more buyers to visit, increasing the match quality and willingness to pay of the buyer who is keenest *ex post*. This result extends to a setting when the seller does not have all the bargaining power. Thus, in this analysis, the role of asking price is to encourage visits. See also Green and Vandell (1998) and Arnold (1999) who also treat the asking price as a ceiling.

Our paper's model of commitment and search, in contrast, does not treat asking price as a ceiling. It is, thus, consistent with all three stylized facts discussed above. The model establishes that the commitment role of asking price remains, even when it is no longer always a binding ceiling. In the state of the world where the buyer accepts the asking price, the buyer enjoys more surplus than under the alternative regime of negotiating with the seller, which allows the asking price to direct search.

The primary difference between our model and Chen and Rosenthal is that it allows for bidding wars as well as accepting the asking price or negotiating down from it. The effect of asking price on visitor utility is different in this case than in Chen and Rosenthal in that buyer utility no longer rises monotonically as asking price is reduced. A decrease in asking price increases the likelihood of a bidding war, so eventually a lower asking price provides visitors with less rather than more probability of encountering a binding ceiling. This translates directly into buyer visit behavior. A seller can encourage more visits by reducing the asking price from the maximum of the support of the buyer value distribution. At some point, however, a reduction in asking price does not encourage more visits because the asking price reduction increases the likelihood of a buyer with a high valuation facing strong competition.

In addition to modeling the role of asking price, the paper carries out an empirical analysis of asking price by considering these and other predictions of the model. This sort of empirical analysis of directed search is completely new to the housing search literature, since data on actual search activity is very rare. This has forced prior researchers to consider the relationship between asking price and outcomes such as time-on-market, rather than search itself.

In order to carry out our empirical analysis, we make use of survey data collected by Genesove and Han (2012b) from a large North American metropolitan are. These data are unique in including the number of bidders on a house, which we use as a proxy for the number of buyers who have a serious interest in purchasing the house. The number of serious bidders is, of course, itself a subset of the number of visitors, and so it captures only part of aggregate buyer search activity. Consistent with the model, we find that a lower asking price increases the number of bidders. Moreover, the negative relationship between asking price and number of bidders is stronger in a bust market than in a boom market. In addition, the asking price also has a stronger effect for an atypical house, as the model predicts. The latter two results come directly from the theory. Finally, we find that in a boom there are fewer below list sales and more transactions with sales price equal to and above asking price.

The paper contributes to the growing literature on housing market microstructure. See Han and Strange (2015) for a recent survey. Our partial equilibrium model of a home seller's problem builds on a long tradition of models of this sort, including Stull (1978), Salant (1991), Green and Vandell (1998), and Arnold (1999). As with Chen and Rosenthal (1996a,b), these papers all deal with the fundamental tradeoff where a reduction in asking price increases visits to the house or the probability of sale. In this context, it has been shown that booms impact housing search (e.g., Novy-Marx, 2009), the negotiation over sales price (e.g., Carrillo, 2013), and future home price appreciation (Carrillo et al, 2015). It has also been shown that the seller of an atypical house is likely to have a longer time-on-market (Haurin, 1988). While these random matching models motivate both our theory and empirical work, there is no role for asking price in the search process. None of these papers deals with the possibility of a price above asking price.

The important recent general equilibrium model of Albrecht et al (2014) is a notable exception. It presents a directed search model in housing where the asking price is also not a ceiling, and the sales price can be above, below, or equal to the asking price. Unlike the partial equilibrium models described above, Albrecht et al allows for competition among sellers to attract visitors. In the case where sellers differ in motivation, they show that there is signaling associated with asking price, implying a particular sort of competition among houses. In Albrecht et al, a lower asking price attracts more visitors, as it also does in the partial equilibrium models.

Empirical work on directed search is much less common. This is because data sources used in empirical research nearly always provide data on outcomes, such as time-on-market or price, rather than on the search process itself. See, for instance, Zuehlke (1987), Sass (1988), Yavas and Yang (1995), Genesove and Mayer (1997, 2001), Knight (2002), Anglin et al (2003), Merlo and Ortalo-Magne (2004), and Haurin et al (2010). These papers conclusively establish the existence of a positive relationship between asking price and time-on-market. Only a few empirical papers have dealt with search activity directly. Carrillo (2012) estimates a structural model of search, which is employed to estimate the effects of increases in the information contained in listings. In the Genesove and Han (2012b) analysis of search, the focus on the dispersion in buyers' valuations for the same house rather than on the directing role of asking price, as in this paper. Merlo et al (2015) make use of data on offers made by buyers and seller revisions of asking price to model the negotiation process. Our empirical analysis is similar in being based on data on actual search activity, although we adopt a reduced-form approach. Our results on the directing role of price and the role of market conditions and atypicality are unique to this paper.

The remainder of the paper is organized as follows. Section II documents the stylized facts of asking price as a way to motivate the paper's theory. Section III presents the model, while Sections IV and V solve for its equilibrium. Section VI then takes the predictions of the model to housing market data. Section VII concludes.

II. The stylized facts of asking price

As noted previously, Case and Shiller (1988) provide some rare early evidence on the fractions of house sales where price is above-, below-, or equal to the list price. We reproduce the Case and Shiller evidence in Table 1. The four-city average shows that all three types of sales take place in nontrivial fractions, with 4.9% of sales above list, 27.9% of sales at list, and 67.1% below list. There is notable variation among markets. For above-list sales, the fractions in Los Angeles and San Francisco were 6.3% and 9.8%, respectively. The fractions were lower in Boston and Milwaukee at 0.5% and 3.3%. For our purposes, we care particularly about the share of transactions where sales price equals list price. These shares are 38.0% for Los Angeles, 26.8% for San Francisco, 23.5% for Boston, and 22.7% for Milwaukee.

Case and Shiller (2003) revisit these cities and present evidence of how the nature of housing transactions had changed by the time of the great boom that took place in the first part of the 2000s. This evidence is also reproduced in Table 1. The shares of above-list and at-list sales are both considerably greater, with a four-city average equal to 25.5% and 48.4%.

The significant shares of above-list and at-list sales documented by Case and Shiller (1988, 2003) are roughly consistent with the evidence from a more systematic buyer and seller survey conducted by the National Association of Realtors (NAR).[4] Table 2 presents the NAR-reported shares of below- and at-list sales over the period 2003-2010. We report results of three subsamples: a sample of recent homebuyers, a sample of recent home sellers, and an aggregate sample that includes both buyer and seller responses.[5] Over the 2003-2006 period when the housing market was in a boom, the table's aggregate sample results (which contain responses from both buyers and sellers) show that the share of below-list sales was about 57%, while the share of acceptance sales was close to 30%. Turning to the 2007-2010 bust, the share of below-list sales increased to about 74%, while the share of acceptance sales reduced by almost a half. The buyer and seller samples exhibit similar patterns. This boom and bust variation in the below-list and acceptance sales are consistent with the Case-Shiller surveys.

Together, these two tables motivate our theory. In understanding the role of asking price, it is necessary to have a model that allows the possibility of below-, above-, and equal-to-list price sales. The model will show that asking price retains the ability to direct housing search despite this. As discussed in the Introduction, this ability comes from asking price representing a commitment from the seller in certain circumstances and thus rewarding and encouraging buyer search. The model will have predictions about

[4]A detailed description of the NAR survey is provided in Genesove and Han (2012a) and Han and Strange (2014). The NAR surveys are biannual from 1987-2003. They are annual starting in 2003. We have reported results only for the latter period. The earlier NAR surveys have shares of below-list, above-list, and at-list sales that are similar to those reported in the Case-Shiller (1988) four city survey.

[5]The survey targets only buyers, but buyers are asked if they have recently sold a home. If so, they are asked about their sale as well as about their purchase. This creates the seller sample.

the patterns of the asking-price-search relationship and the nature of housing transactions in booms and busts. Testing these predictions requires data on buyer search activity. Such data are not present in either the Case-Shiller surveys or the NAR survey or any other standard housing market data source. In Section VI, we will introduce a novel data source, the Genesove-Han (2012b) survey, a dataset that contains detailed information on both house characteristics and search activity. This will permit an empirical test of the predictions generated from the model laid out in the next section.

III. Model

This section specifies a partial equilibrium model of housing market microstructure that allows us to establish the commitment role of asking price when it is neither a posted price nor a floor nor a ceiling. We work with a one period model where the seller initially sets an asking price, buyers subsequently make choices of whether or not to visit, and the house is ultimately sold as a process of negotiation. We have chosen this specification because it allows for both the possibility of traditional negotiations between one buyer and a seller and also the more current practice of having multiple simultaneous offers on a house. A standard arrival model would preclude the latter possibility.

The model captures the decisions made by an individual home seller, as in Stull (1978), Salant (1991), and especially Chen and Rosenthal (1996a,b). The seller has a reservation price of x_L. There exists a heterogeneous pool of potential buyers for the house. Each buyer's reservation price for the house, x, is a draw from the set $\{x_L,x_H\}$. The probability that $x = x_H$ is δ. The probability that $x = x_L$ is $(1-\delta)$. A buyer's reservation price should be interpreted as the idiosyncratic value of the particular house to the buyer who has visited it. We suppose that x is revealed to both buyer and seller only after the buyer visits the house.[6] There are two costs associated with a buyer's visit to a house. A visit has cost c to the buyer and cost s to the seller. Buyer search costs include the time and money costs of inspecting the house. Seller search costs include the time and money costs of preparing the house for a buyer's visit and of absenting oneself during it.[7] These are incurred prior to learning whether or not the house is a good match. We suppose that all agents – both buyers and sellers – are risk neutral.

After search, the sales price is determined. Suppose for now that there is no asking price. In this case, the seller and one or more buyers will negotiate over the price. In the case where there are two or more buyers who are high type, then the price will give all the surplus to the seller regardless of asking price, and $p = x_H$. In the case where there are no buyers who are high type, then there is no surplus to split,

[6] This assumption makes the analysis of bargaining between buyer and seller much more transparent.

[7] The seller's costs are incurred when the buyer chooses to visit. The seller will be able to select the number of visits through the asking price, as described below. Since the visits are frequently spread out in time, we have assumed that each visit has a positive marginal cost to the seller.

and $p = x_L$. In the case where the seller negotiates with exactly one high type buyer and one or more low type buyers, then the price depends on the relative bargaining power of the participants in the transaction. Let $\theta \in [0, 1]$ denote the seller's bargaining power. In this case, a negotiation between a seller and one high type will result in a price of $p = \theta x_H + (1-\theta)x_L$. This outcome does not depend on the presence of low-type buyers. This conception of bargaining is an important and, we believe, empirically grounded feature of our model. In our one-period model, bargaining captures, at least to a degree, the different options that market participants can expect if a transaction is not consummated.

In order for asking price to matter, two conditions must hold. First, the asking price must be low enough. Let $a_\theta \equiv \theta x_H + (1-\theta)x_L$. The critical level a_θ is the maximum asking price that would be as good as negotiation. It is in this case that the asking price is relevant since the good-match buyer would prefer to accept the asking price rather than negotiate. Whether this condition holds will be determined by the seller. Second, the asking price must entail some sort of commitment. As noted elsewhere in the literature, there is usually not a legal requirement that a seller transmits a house to a buyer who makes an offer at or equal to the asking price. However, sales agreements with listing agents typically require a seller to pay the agent's commission in the event of rejecting an at-or-above list offer without restrictions. So a seller may incur costs for rejecting an offer that is at or above the asking price. Furthermore, the rejection of an offer equal to or above asking price clearly fails to conform to standard notions of good faith bargaining.[8] A seller might assign costs to such behavior. In addition, it is easy to see how the seller or the seller's agent would be viewed cautiously by other buyers and buyer agents. However, if multiple buyers offer more than the asking price, there is no peril for the seller agent's commission and there is no clear bad faith on the part of the seller or the agent. We therefore suppose that the asking price is a commitment as long as there are not multiple buyers willing to pay more for the house.

The timing of decisions and events is as follows. First, seller sets asking price taking s as given. Second, the buyers sequentially choose whether to visit knowing only a, c, and the distribution from which x is drawn. Let n be the number of visitors. Third, the x values are revealed to both buyers and sellers. Fourth, the price is determined by bargaining or by the acceptance of the asking price, as above.

IV. How asking price directs search

A. Pricing: when does a price ceiling bind?

This section will show how asking price can direct search, despite being neither a posted price nor a ceiling nor a floor. The first step in doing so is to consider the determination of price after a number of

[8] See, for instance, Frey and Pommerehne (1993) who show that price increases unrelated to cost increases are very commonly perceived as unfair.

buyers have visited the house. Suppose initially that n =1, so there is one visitor. Suppose for now that $a \in (x_L,x_H)$. We will consider the possibility of asking prices equal to x_L and x_H below. If $x = x_L$, then $p = x_L$. If $x = x_H$, then the high type sole visitor would accept the asking price if and only if $a \leq a_\theta = \theta x_H + (1-\theta)x_L$. This illustrates an important point made by Chen and Rosenthal: the asking price is valuable to buyers as a commitment only if their bargaining power does not already enable them to command a lower price. Put another way, the asking price must be low relatively to the price that a buyer's bargaining power would already allow to be realized.

Suppose now that there are $n \geq 2$ visitors. There are three relevant cases at the price determination stage. In the first case, all values of x are less than or equal to a. Since $a \in (x_L,x_H)$, this requires $x = x_L$ for all the visitors. Since $p = x_L$ and whichever visitor who buys the house has a valuation of x_L, in this case, buyer utility equals zero, as does seller profit.[9] We will call this the *traditional case*, since it corresponds to the setting of a high asking price and then negotiating down, as was the common practice in housing sales in most markets through the 1990s. Let τ denote the probability of traditional case outcome of sales price being strictly below asking price. By construction, we have $\tau = (1-\delta)^n$.

Obviously, this is an extreme version of the traditional case. With a continuous support for buyer valuations, the price – and thus the utility of the winning bidder and the profit of the seller -- would depend on the distance between the first and second order statistics of x. We have adopted the discrete specification because it clarifies the role of asking price. The results of a continuous specification are similar, if less clear. They are discussed below, with details presented in the online Appendix A.

In the second case, multiple visitors draw match values in excess of the asking price. This requires that at least two buyers have valuations equal to x_H. In this *bidding war case*, as in the traditional case above, there is no surplus for buyers. As noted above, $p = x_H$, giving buyer utility of zero and seller profit of $x_H – x_L$. The bidding war is qualitatively similar to the traditional case in that only the seller enjoys a positive surplus. The commitment in the asking price does not bind when multiple bidders take the price above the asking price. As above, that a bidding war gives zero surplus is a consequence of the discrete specification.

In the final case, only one buyer draws a match value above the asking price. In this *acceptance case*, the commitment binds for a high type buyer when bargaining power is not too great and $\theta x_H + (1-\theta)x_L \geq a$. If the commitment does bind, the utility of a high type buyer is $x_H - a$, while the seller's profit is $a – x_L$. The probability of acceptance is the probability that exactly one buyer is willing to pay more than the asking price, while all the others draw lower values. The probability of the acceptance case, denoted by α,

[9] It is natural to suppose that with n buyers willing to pay x_L for the house, one of them is randomly selected as the winner. Of course, the structure of the pricing process means that both the winning buyer who ends up with the house and the losing buyers have zero utility.

is therefore equal to $n\delta(1-\delta)^{n-1}$. This implies that the probability of the bidding war case, denoted by β, equals $1- (1-\delta)^n - n\delta(1-\delta)^{n-1}$.

This situation is summarized in the following:

Proposition 1. When $a \in (x_L,x_H)$ and $n \geq 2$, there are positive probabilities of below-, above-, and at-list price sales.

Proof: See the probabilities above.

As long as there are some visitors and the asking price is between the value of good and bad matches, the model allows for all three of the possibilities illustrated empirically in Section II. It is possible that sales price exceeds asking price. Or sales price may be above asking price. Or a buyer may accept asking price and thus sales price will exactly equal asking price. All three of these possibilities are clearly empirically relevant, so any model of housing market microstructure should allow for all the cases. Despite the possibility that sales price might be above or below asking price in equilibrium, we will show below that asking price continues to matter as a commitment that binds in some situations.[10]

We have thus far considered the case where $a \in (x_L,x_H)$. Suppose instead that $a \geq x_H$. Since $a_\theta < x_H$, any asking price at or above x_H will have the same outcome that would come from an asking price equal to a_θ. There is, thus, nothing gained from setting such a high asking price, and we can ignore them. Suppose now that $a \leq x_L$. In this case, if two or more buyers draw $x = x_H$ we will still have $p = x_H$ as above. If instead all the buyers draw $x = x_L$, we will still have $p = x_L$, again as above. The only difference is if exactly one buyer draws $x = x_H$. With $a \leq x_L$ we no longer have the situation above where only one buyer wanted to accept the asking price which we argued made it a commitment. We now have both low and high type buyers who would be at least weakly willing to accept the asking price. In this case, we suppose that the house goes to the high bidder at $p = x_L$. We believe that this technical assumption is reasonable in the sense that the house goes to the high valuation buyer at a price beyond which other buyers will not bid. With this and an additional assumption introduced later, it will be shown below that setting an asking price equal to or below x_L is dominated for the seller. This is why we focus on $a \in (x_L,x_H)$.

The expected sales price of the house equals $\alpha a + \beta x_H + \tau x_L$. It is thus possible for asking price to directly impact the ultimate sales price since it enters directly into the first term of the price equation. This is not the only potential impact of asking price. In the next section, we will show how the seller's choice of asking price will impact buyer search and therefore indirectly affect the expected sales price.

[10] It is worth observing that in this setup there is zero probability of a house failing to sell. It would be easy to change the model in a way that would generate illiquidity by supposing that $x_L > 0$ and that there is a positive probability of a visitor drawing $x = 0$. This modification would not change any of the model's other properties.

B. Visiting

A buyer visits when the expected utility of search exceeds the cost, taking as given the search choices of the other buyers. The equilibrium number of visits must give visitor n expected utility greater than or equal to search cost and visitor n+1 expected utility less than search cost. We are assuming here that buyers are aware of the interest of other buyers. We believe that this is realistic; real estate agents assisting buyers and sellers routinely inform their clients of the market's interest in particular properties.

As noted above, buyer bargaining power allows them to retain some of the value created by search. The greater is buyer bargaining power, the greater is the incentive for search and the lower must be the asking price in order to give an additional search incentive. Suppose that asking price is irrelevant, with $a \geq a_\theta$. The first buyer who searches a given house has positive ex post utility only when she is high type (probability δ). This means that expected utility, υ, is given by

$$\upsilon = \delta[x_H - \theta x_H - (1-\theta)x_L] = \delta(1-\theta)[x_H - x_L] \qquad \text{(IV.1)}$$

This equals the probability that a buyer is high type times the negotiated share of surplus.

If expected utility when only one buyer visits is less than search cost c, then there will be no visits at all, and the house will not sell. Setting expected utility equal to search cost thus gives a necessary condition for a positive number of visitors:

$$\delta(1-\theta)[x_H - x_L] \geq c. \qquad \text{(IV.2)}$$

Our goal is to focus on the role of asking price. Chen and Rosenthal simplified their base model with the strong assumption that the seller had complete bargaining power, $\theta = 1$. In this case, the only way to get a buyer to search is to use the asking price as a ceiling.[11] In a similar spirit, we will employ (IV.2) to specify an assumption on bargaining power that gives a minimum level of θ so that at least one buyer will search. Formally, we suppose:

Assumption 1 (weak buyer bargaining power): $\theta \geq 1 - c/[\delta[x_H - x_L]]$

Assumption 1 implies that the seller is forced to employ the asking price to encourage search since otherwise no buyers are willing given their weak bargaining power.

[11] They later show that their analysis follows with some modification under weaker bargaining assumptions.

To understand the role of asking price in this setup, we begin by considering the first buyer's search. The first buyer who searches would obtain expected utility equal to

$$\upsilon_1 = \delta[x_H - a], \tag{IV.3}$$

since the probability (1-δ) event of a low realization of house value is associated with zero surplus. Setting expected utility from (IV.3) equal to search cost defines the maximum level of asking price that would encourage one buyer to visit:

$$a_1 = x_H - c/\delta. \tag{IV.4}$$

Moving on to the case of $n \geq 2$ visitors, there is zero expected utility in both the traditional case (where both the price and valuation are x_L) and the bidding war case (where price and valuation are x_H). This means that the probability that some buyer gets positive expected utility is the probability of the acceptance case. The probability that a given buyer gets positive expected utility is (1/n) times the probability of the acceptance case. Thus, expected utility with n visitors is

$$\upsilon_n = (1-\delta)^{n-1}\, \delta[x_H - a]. \tag{IV.5}$$

Setting this equal to c defines the maximum asking price such that n buyers visit:

$$a_n = x_H - c/[\delta(1-\delta)^{n-1}]. \tag{IV.6}$$

(IV.6) defines the inverse "demand" schedule that a homeowner faces as the sequence of asking prices $\boldsymbol{A} = \{a_n \mid n=1,2,\ldots,N\}$. The demand schedule is drawn in Figure 1. For $a \in (a_1,x_H)$, the asking price is high enough that no buyers visit. For $a \in (a_{n+1},a_n]$, n buyers visit. In order for search to be attractive at all, set the utility for the buyer with n = 1 from (IV.4) equal to search costs. This gives a relationship between the probability of a good match and the surplus from a good match and search costs: $[x_H - a] \geq c/\delta$. For reasons discussed above, we only need to consider asking prices $a \in (x_L,x_H)$. The lowest possible value for asking price a is thus, x_L. This gives a condition that makes it possible for one buyer to benefit from search:

Assumption 2 (potentially valuable search): $[x_H - x_L] \geq c/\delta$.

In this case, it is possible to set an asking price that encourages at least one buyer to visit. We suppose that Assumption 2 holds.

The key aspect of the demand schedule is that it captures how an asking price that is not a posted price, ceiling, or floor can direct the search process. The first and most important implication is that *a lower asking price is required in order to encourage more visits*. This can be seen from taking the derivative of (IV.6) with respect to a:

$$\partial n/\partial a = [1/\ln(1-\delta)]\,[1/(x_H - a))] < 0. \tag{IV.7}$$

This result extends the Chen-Rosenthal (1996a,b) price ceiling result. In our model, asking price directs search even though it is not a rigid price ceiling.

A second noteworthy property of the demand schedule is that *the amount of search that can be provoked by reducing the asking price is bounded*. Formally, the maximum number of visits that can be encouraged, N, is defined by

$$[x_H - x_L] = c/[\delta(1-\delta)^{N-1}]. \tag{IV.8}$$

This contrasts with the Chen-Rosenthal model of a price ceiling. There, a reduction in asking price always increases the payoff to investigating a house and thus increases expected search activity. In our model, in contrast, asking price is not a ceiling. This means that reducing asking price below x_L has no effect on surplus. If there are multiple buyers willing to pay x_H or there are multiple buyers willing to pay x_L, both of which result in bidding wars with the successful buyer obtaining zero surplus. What all of this means is that when asking price is not a ceiling, reducing asking price beyond a certain point does not encourage more visits since there is sure to be a bidding war, rendering the asking price irrelevant in such a case.

These properties of the demand schedule are summarized in the following:

Proposition 2: For a $\in (x_L, x_H)$, the number of visits weakly increases as asking price falls until reaching a bound beyond which further decreases of asking price do not encourage more visits.

Proof: See above.

Proposition 2 characterizes the downward sloping demand schedule faced by a home seller. It is similar to prior results from partial equilibrium models where a lower asking price also encourages more visits. The extension here is that our model does not treat asking price as a ceiling. The general equilibrium model of Albrecht et al (2014) also allows for the possibility of sales prices being higher than asking price and obtains the result that visits can be encouraged by a reduction in asking price. In the Albrecht et al model, a reduction in asking price can encourage visits when it signals seller motivation. In equilibrium, a low asking price can lead buyers to believe that the seller has a lower reservation price. This encourages visits because potential visitors anticipate a larger expected value from a possible match with a seller who has a low reservation price. As with our model, a lower asking price encourages more visits by raising expected match value, although the link between asking price and expected match value is different.[12]

The comparative static properties of the demand schedule are also worthy of discussion. First, the elements of the demand schedule, a_n, decrease in c. This is immediate from differentiating (IV.6). Higher search costs require even lower asking prices to encourage a given number of visits. Second, the elements a_n increase in x_H. When a good match is worth more, then there is greater search for any level of asking price. Since both of these variables are associated with greater demand for any given house (more search), they will be useful below in considering how asking price operates in boom and bust markets. Third, the maximum possible number of visits, N, is decreasing in buyer search cost c and increasing in good match quality x_H by (IV.8).

In contrast, the effects of δ, the probability that any particular buyer obtains a good match, are ambiguous. For n =1, (IV.4) implies that if δ equals zero, there will be no visits since there is never positive buyer surplus for any asking price. An increase in δ allows a larger asking price since the buyer's surplus has increased. For $n \geq 2$, (IV.6) there is an ambiguous relationship. As n becomes large, the relationship eventually becomes negative. This is because the probability of a buyer competing in a bidding war with other well-matched buyers rises with δ. We will return to this issue below when we consider the relationship between housing market conditions – boom or bust – and the asking price.

Continuing with comparative statics, a further investigation of equation (IV.7) shows that

$$\partial^2 n/\partial a \partial x_H = -[1/\ln(1-\delta)][1/(x_H - a)^2] > 0 \qquad \text{(IV.9)}$$

and

$$\partial^2 n/\partial a \partial \delta = [1/(1-\delta)][1/\ln(1-\delta)]^2[1/(x_H - a)] > 0. \qquad \text{(IV.10)}$$

[12] Signaling takes place only when sellers are heterogeneous in an unobserved way. In the case where sellers are homogeneous sellers, Albrecht et al obtain the sharply different result that visits are unrelated to asking price in equilibrium as long as asking price is above seller reservation price. In this setting, asking price is indeterminate, as long as it exceeds reservation price.

(IV.9) indicates that the greater is the value of a good match, the weaker is the negative effect of the asking price on the number of bidders. (IV.10) shows that the larger fraction is the high type buyers, the weaker is the negative effect on the number of bidders.[13]

These comparative static results are summarized in the following:

Proposition 3: The critical level of asking price needed to attract n visitors decreases as search cost rises and as the value of a good match falls. The responsiveness of the number of visitors to a decrease in asking price rises as the value of a good match rises and as the probability of a good match rises.

Proof: See above.

The results on the marginal effect of asking price on search are helpful in analyzing directed search in booms and busts. An increase in x_H is a very natural way to conceive of a boom: the value of good matches has increased. Likewise, an increase in δ is also a natural way to conceive of a boom: the probability of a good match increases. Proposition 3 means that in boom, asking price has a smaller role in directing search. The intuition is that in a boom, the surplus that a buyer anticipates from visiting is large, and this reduces the necessity of using the asking price to attract visitors. Thus, search direction is stronger in a bust than it is in a boom.

The comparative statics in Proposition 3 are also important for the light they shed on the heterogeneity of housing. That housing is a highly differentiated product is well understood. Some houses, however, are more heterogeneous than others. Condominiums and mass-produced tract housing are relatively homogeneous. Single-family houses and other customized housing are relatively heterogeneous. An understanding of the housing market requires an understanding of how these different market segments transact. The standard approach to considering this issue is suggested by Haurin (1988), who defines a house's atypicality based on the differentiation of its attributes from other houses.

There are two ways that our model can capture atypicality. One is that less typical houses are less likely to be good matches for a household that visits them. Formally, δ is lower. In this conception, atypical houses will exhibit a stronger relationship between asking price and the number of visits. Alternatively, less typical houses can be conceived as having greater dispersion in match value. Formally, δ is lower and x_H is greater (holding x_L fixed). In this conception, less typical houses will have an ambiguous relationship to the number of visits.

[13] See the online Appendix B for a numerical example of the demand schedule, including these comparative static properties.

These findings on the variation in search direction are important for a number of reasons. First, they are important to housing economists interested in directed search because the results on atypicality and booms and busts extend previous research on the role of the asking price. This research showed a robust relationship between market conditions and time-on-market. It also demonstrated a relationship between atypicality and time-on-market. Atypical houses are less liquid, and there is less liquidity in a bust. Houses with high asking prices relative to their characteristics are also likely to experience a longer time-on-market. The results here offer a significant and novel extension by showing how the importance of asking price varies in the context of a micro-founded model of asking price. Second, the results are relevant to the marketing of houses. Home sellers are often advised to set "competitive" asking prices.[14] The results here show that this approach will have a greater payoff in busts than in booms. This is clearly relevant to marketing houses. Similarly, the analysis here shows that atypical houses may also face different environments that impact their marketing. The relationship is ambiguous in theory, however, and understanding it will require empirical analysis. We will consider this empirical relationship below, as well as the relationship between booms and busts and the directing role of asking price. Before coming to these topics, however, we need to consider the seller's choice of asking price.

V. The house seller's choice of asking price

The seller sets asking price to maximize expected surplus taking the relationship between n and a as given. Suppose that the seller chooses an asking price that leads to n = 1. In this case, expected profit is

$$\pi_1 = \delta[a - x_L] - s. \tag{V.1}$$

With n = 1, the seller would set $a = a_1$ from (IV.4). Substituting this into (V.1) and simplifying gives a condition on both buyer and seller search costs that must be required in order for a seller
to able to profit from listing the house

Assumption 3 (potentially valuable transaction): $[x_H - x_L] \geq (c+s)/\delta$.

To rule out this uninteresting case, suppose that Assumption 3 is met. This ensures that at least one visit is profitable from the seller's perspective

For an asking price that leads to $n \geq 2$, expected profit is

[14] See Barta (2003) at http://www.wsj.com/articles/SB121380010708384369 for an example of this sort of advice.

$$\pi_n = n(1-\delta)^{n-1}\delta[a_n - x_L] + (1-(1-\delta)^n - n(1-\delta)^{n-1}\delta)[x_H-x_L] -ns. \quad \text{(V.2)}$$

The first term is the probability of acceptance times the payoff to the seller. The second is the probability of the bidding war times the payoff. Substitution of the asking price from (IV.6) and rearranging gives profit as

$$\pi_n = (1-(1-\delta)^n)[x_H-x_L] - (c+s)n. \quad \text{(V.3)}$$

It is straightforward to see that the seller will choose from the demand schedule $\boldsymbol{A}$. Choosing any other asking price gives the same number of visits as an element of A but has lower expected profits by (V.1) and (V.3).

Let the sequence of expected profits be given by $\boldsymbol{\Pi} = \{E\pi_n \mid a_n \in \boldsymbol{A}\}$. The seller thus chooses an element of the asking price sequence $\boldsymbol{A}$ to obtain the maximum of Π. Since $\boldsymbol{\Pi}$ is a finite set, it has a maximum element. In characterizing this optimal asking price, the difference between profit at n and profit at n-1 will be crucial:

$$\Delta\pi_n = \pi_n - \pi_{n-1} = (\delta(1-\delta)^{n-1})\,[x_H-x_L] - c - s. \quad \text{(V.4)}$$

We have already noted that $\pi_1 > 0$ by Assumption 3. This implies $\Delta\pi_n > 0$. Denote the first term of (V.4) by

$$\phi = (\delta(1-\delta)^{n-1})\,[x_H-x_L]. \quad \text{(V.5)}$$

It is straightforward to establish that $\partial\phi/\partial n < 0$. Furthermore, at the maximal number of visits, N, we have $\phi - c = 0$ by (IV.7). This means that for $s > 0$ the maximizing asking price is associated with a number of visits $n \leq N$. The maximizing asking price a_n^* will satisfy $\Delta\pi_n > 0$ and $\Delta\pi_{n+1} > 0$.

We previously asserted that a seller would not want to set an extreme asking prices at either x_L or x_H. It is now possible to confirm this. First, an asking price equal to x_H leads to zero visitors by (IV.4). It thus is dominated by any asking prices that elicits positive numbers of visits. Second, an asking price equal to x_L is dominated unless $x_L = a_N$ for the maximum possible number of visits, N. It is thus au knife edge case where $a = x_L$ fails to be dominated. We will thus suppose $a_N > x_L$.

Since the seller's optimal asking price is on the interior of (x_L,x_H), the probabilities of the traditional, bidding war, and acceptance cases are all positive. This model thus shows that asking price can have a commitment role, encouraging search, even when the asking price is clearly neither a posted price nor a strict price ceiling:

> Proposition 4: Under Assumptions 1, 2, and 3 (weak buyer bargaining power, potentially valuable search, and potentially valuable transaction), the seller's optimum asking price encourages a positive amount of buyer search (number of visitors).
>
> Proof: see above.

Proposition 4 describes a situation where there is a unique optimal asking price that directs search, even though sales price can be above-, below-, or at- the asking price.[15]

This leads to the question of how these three types of sales are impacted by market conditions and by house characteristics. In a bust, asking price has a stronger directing effect on search. Similarly, a reduction in asking price leads to a greater increase in visits for an atypical house. How do these circumstances impact whether a house sells above-, below-, or at-the asking price?

The probability of a below-list traditional sale has been defined as $\tau = (1-\delta)^n$. It is well-established that a boom features lower time-on-market. This is consistent in our model with a greater number of visits. An increase in x_H, for instance, will lead the seller to reduce asking price, leading to a larger n by (V.4). This suggests that one should expect a boom to lead to a reduced share of below-list sales. Similarly, the probability of a bidding war, $\beta = 1- (1-\delta)^n - n\delta(1-\delta)^{n-1}$, will be greater with a larger n. The probability of acceptance, $\alpha = n\delta(1-\delta)^{n-1}$, has an ambiguous relationship to the number of visitors. We empirically assess the effects of booms and busts on housing transaction types in Section VI.[16]

Atypicality also has the potential to impact transaction type. Haurin (1988) shows that atypical houses experience longer times-on-market. Interpreting this, as above, as a decrease in the number of visits suggests that an atypical house would be more likely to sell in a traditional below-list transaction. It would be less likely to sell in a bidding war. The likelihood of an acceptance is, has an ambiguous relationship to the number of visits and to atypicality. We also empirically assess these predictions in Section VI.

Before turning to the empirics of asking price in the next section, there are several points that should be made about the asking price model. The first concerns the model's discrete specification. The

[15] In Albrecht et al (2014), asking price also directs search, in this case by signaling the motivation of sellers. Within any group of equally motivated sellers, there are multiple equilibria in Albrecht et al, in contrast to our model.

[16] It is worth noting that there are other forces at work that link the state of the housing market to the choice of asking price and the transaction type. Genesove and Mayer (1997) show that sellers with high loan-to-value ratios set high asking prices and experience longer time-to-sell. Genesove and Mayer (2001) show that sellers who have experienced nominal losses also set high asking prices and have long times-on-market. Since busts are characterized by both low seller equity and sellers who have suffered losses, both of these forces will lead to higher asking prices in busts.

specification's most important consequence is that any visitor will be either a good or bad match with the seller's house. We have adopted this specification because it allows us to obtain analytical solutions for most (although not all) of the aspects of the housing transaction in which we are interested. If we instead had supposed the match quality x to be drawn from a continuous probability density, then the most important results would continue to hold. Details are presented in the online Appendix A. In the continuous case, there would continue to be three possible types of house sale, all of which occurring with positive probability as long as there are $n \geq 2$ visitors. The asking price would continue to have a directing role in the search process despite not being a fixed price or even a ceiling. The most important difference is that the bidding war phenomenon renders the demand relationship non-monotonic even on the interior of $[x_L, x_H]$. For a low enough asking price, the primary effect of a further reduction is to increase the probability of a bidding war, and this fails to encourage additional visits under the assumption of weak bargaining power.

Second, we have thus far assumed buyers to have weak bargaining power (Assumption 1) in order that we might focus on how asking price can direct search. As noted above, buyer bargaining power and asking prices are substitutes in their role in search. It is worth exploring how relaxing Assumption 1 would impact the analysis. Beginning with the most extreme failure of Assumption 1 to hold, suppose that buyers have complete bargaining power, $\theta = 0$. In this case, the price will never exceed x_L, and asking price has no effect at all on search. As buyer bargaining power rises, a_θ rises. If $a_\theta \in (a_{i+1},a_i)$, then there will be at least i visitors regardless of asking price. The seller can encourage further visits by lowering asking price to a_{i+1} or lower. At this point, we turn to the empirics of directed search in housing markets.

VI. The empirics of asking price.

A. Data

The NAR surveys have the advantage of covering a large number of markets over a long period of time. However, they are not well-suited to testing the key predictions of the model about search. This is because they do not include variables that measure the amount of search targeted towards a particular house and also because the NAR data set includes only coarse controls for house quality, which can create problems for the estimation of the relationship between asking price and search activity. We will therefore work with an alternate data source in this section.

Our primary data are based on a survey of recent buyers in a large North American metropolitan area, conducted by Genesove and Han (2012b). To conduct surveys in this metropolitan area, Genesove and Han take the addresses of buyers from transaction records of single-family homes available at the local Multiple Listing Service (MLS), covering one-third of the area. Names of these buyers are purchased from the deeds office. From the universe of transaction records, mail samples of 4,021 were drawn at random for

2006, 4,580 for 2007, 6,909 for 2008, and 3,279 for the first three quarters of 2009. The overall mailing list contains 18,789 addresses, out of which 1,816 addresses are invalid for survey purposes. Among these invalid addresses are some who bought land only, some as institutional buyers, etc. With these excluded, the total number of questionnaires we sent out in the first round is 16,973. A total of 351 surveys were returned "households-moved" or "address unknown" by the Post Office. In total, 3,193 valid interviews have been conducted, among which 1,722 by mail and 1,467 by phone interviews conducted by our research assistants. The overall response rate so far is 19.2%.

To the best of our knowledge, this survey is the only dataset that provides information on home search, bargaining and bidding behavior. Although the response rate of 19.2% seems low, it is quite comparable to the average response rates of surveys conducted by the National Association of Realtors, which have been the basis of almost all other surveys of buyers. In particular, the NAR response rate never exceeded 29% and fell as low as 6% in some years. In total, we collect 3,193 returned questionnaires, which gives us a much larger sample than the well-known Case-Shiller surveys.[17]

Of course, whether or not the response rate of 19.2% leads to self-selection bias depends on the pattern of survey response. One possibility is that the propensity to respond to the survey is correlated with the subject's economic and demographic characteristics. For example, high-income people have higher opportunity costs of time, making them less likely to respond to the surveys. Higher opportunity cost also implies higher search cost, which strengthens the directing role of the asking price on buyers' search process. To see this, consider an extreme case where there is no search cost. In this case, buyers will visit all houses of interest, which leaves no directing role for the asking price. In this regard, by omitting the high-cost buyers from the sample, our estimate actually underestimates the true responsiveness of potential buyers to the asking price.

In this market, sellers initiate the search process by listing the property. The Realtor version of the MLS listing usually indicates that offers will be accepted beginning on a particular date, usually 5-7 days after listing. Most houses are purchased at a later point in time. While there are occasionally "bully" offers made earlier, buyer agents will typically "present" legal offers on the date specified in the listing. There may be multiple rounds of offers. Bidders do not meet with each other, and they also do not meet with the seller directly. Potential buyers will consult with their agents prior to bidding, discussing among other things the competition that they are likely to face from other bidders. In this environment, bidders usually register their intent to bid prior the quasi-auction, so bidders will frequently know the exact number of competing bidders. In some cases, only one bidder emerges, and price is negotiated. In others, there are multiple bidders. In both cases, asking price directs search activity. This sort of institutional practice is captured in

[17] For example, the Case and Shiller (2003) survey collected 797 questionnaires in four metropolitan areas.

the model developed above. Although there are differences in the specifics of implementation, we believe that the key features of this process are common across markets.

Although the institutions are broadly similar across markets, different markets have, of course, experienced the recent boom and bust quite differently. For instance, Han and Strange (2014) show that many markets have seen growth in the fraction of bidding war sales, but not all. More generally, markets differed in how they experienced the great boom and bust of the 2000s. In the taxonomy of Abel and Dietz (2010), some markets had substantial booms followed by substantial busts, some had one but not the other, and some had neither. Ours was a market with a substantial boom, but not a persistent bust. The market declined sharply around the period of 2008's financial crisis, but it recovered fairly quickly. As with some but not all markets in this group, there was not a wave of foreclosures in our market. Since foreclosures have such important impacts (see Gerardi et al, 2015, and Lambie-Hanson, 2015), the soft landing that our market experienced means that some of our results on the directing role of asking price in a bust might be stronger in other markets where the negative shock was deeper and more persistent.

Returning to the survey itself, two particularly relevant questions are "Were there other people actively bidding on the home when you submitted your first offer?" and "If yes, about how many other bidders were there?" The resulting responses provide information about the number of competing bidders and hence permit an empirical investigation of role of the asking price in directing search. To the best of our knowledge, this information has never been collected previously. Figure 2 shows a histogram of the number of bidders. In two-thirds of sales, there is one bidder. In one-sixth, there are two bidders, and in somewhat less than half of that, there are three bidders. There are more than three bidders in nine percent of the observations. It is clear that this distribution is over-dispersed relative to the Poisson distribution.

The survey data were complemented with publicly available information from the local MLS, which covers 89,891 transactions that occurred in the survey area between 2006 and 2009. Properties are identified in the MLS data by district, MLS number, address, unit number (if applicable). The housing attribute variables include number of bedrooms, number of washrooms, lot front, lot depth, the length and width of the primary room, dummy variables for basement, garage space and occupancy. Inspection of the MLS data reveals that about 2% of observations have more than 5 bedrooms or washrooms. To minimize the impact of these larger houses on the empirical analysis, we drop these observations. Table 3 presents summary statistics of the variable of interest for the merged MLS/survey sample.

Tables 4a and 4b present descriptive patterns for sales price, list price, the number of bidders, and other key outcomes. Three related findings emerge. First, there is a notable fraction of the below-, at-, and above-list sales. This is consistent with the Case-Shiller and NAR Surveys, especially the mass point of at-list sales. Although the acceptance rates in the Genesove-Han Survey are substantially lower, the cyclical variation in the acceptance rates and in the traditional (below list) sales is highly in line with Case-Shiller and NAR.[18] In particular, there is a higher fraction of at-list sales (about 10%) in 2006 when the housing market was in a boom than in 2008 (about 5.5%) when the market slowed down. Second, unlike the Case-Shiller and NAR Surveys, the Genesove-Han Survey presents explicit evidence for the presence of multiple bidders who are interested in the same home. As shown in the last two columns of Table 4a, over one third of buyers we surveyed reported facing competing bidders when purchasing a home. This justifies the bidding war possibility that was modeled in this paper but not in the previous asking price literature. Third, the patterns of bidding behavior are clearly related to the relationship between sales and asking price. Table 4b shows that the number of bidders and the presence of multiple bidders is greater for above-list sales than for at-list acceptances and greater for at-list acceptances than for traditional below list sales. It shows a similar pattern for time-on-market, which is longest for traditional sales. We return to this finding below.

B. Empirical results: The directing role of asking price

The key implication of the model is that a lower asking price encourages more visits. As noted in the Introduction, prior research on asking price has considered outcomes, such as time-on-market, rather than considering search directly. This paper is the first in the literature that provides direct evidence of the effect of asking price on search activity. Specifically, we present a log-linear specification that regresses the number of bidders on the asking price. That is, we estimate the following equation:

$$\ln N_{ijt} = \alpha + \beta \ln P_{ijt} + \gamma X_{ijt} + \eta_t + \tau_j + \varepsilon_{ijt} \tag{VI.1}$$

where N_{ijt} indicates the number of bidders for house *i* in district *j* at period *t*; P_{ijt} indicates the corresponding asking price; X_{ijt} indicates corresponding house attributes;[19] η_t is the year*month fixed effect; τ_j is the district fixed effect. Throughout the paper, we cluster the standard errors at the district level to allow for the spatial and temporal dependence within MLS districts.

The top panel of Table 5 reports the results. Column 1 presents a bivariate regression. The coefficient on the list price is 0.08, positive and significant. Adding transaction period dummies, as shown in Column 2, increases the coefficient to 0.09 but makes it less significant. In Column 3, we add housing

[18]The smaller magnitude of the acceptance rates in our survey could reflect the growing practice in the market under investigation of designating a particular time in a specific day to receive offers. This practice increases the probability of receiving the multiple offers in the same time. It also suggests a lower likelihood of downward revisions in offers, which Merlo and Ortalo-Magne (2004) show to be common, making it somewhat less likely that buyers will report having paid exactly the asking price. Nevertheless, the fraction of acceptance is large enough that it calls for a model to explain the forces at work.

[19] The housing attributes we control for include dummies for the number of bedrooms interacted with dummies for the number of washrooms, lot front, lot depth, the length and width of the primary room, dummy variables for basement, garage space and occupancy.

attributes which increases the coefficient further to 0.14. The positive relationship between the number of bidders and the asking price that we have found so far is hard to interpret in the context of our model. However, this is mostly due to the lack of control on house location. Once we include dummies for the district in which properties are located, the coefficient on the asking price becomes negative and significant, consistent with what we expected. In Column 4, we control for the district dummies only, and the coefficient on the asking price becomes -0.14 and highly significant. Adding transaction period dummies, as shown in Column 5, changes the coefficient to -0.12. Adding housing attributes, as shown in Column 6, further changes the coefficient to -0.22, indicating that lowering the asking price by 10% increases the number of bidders by 2.2%. Together, these results are consistent with the model's key prediction about the role of the asking price in directing homebuyers' search.

The estimated effect of the asking price on search intensity, although qualitatively consistent with the model's predictions, seems small in magnitude. This estimate should be treated as a lower bound for the true directing effect of the asking price for several reasons. First, we use the number of bidders to proxy for the number of visitors. In our stylized model, all visitors bid, but in reality we believe that the large majority of visitors do not bid. This could be captured in the model by supposing that there is a positive probability that $x = 0$. These poorly matched buyers would then not participate in the auction. Since the number of bidders provides a lower bound for the number of visitors, this introduces a downward bias in our estimated responsiveness of the buyers to the asking price, suggesting that the actual directing role of the asking price is even stronger.[20] Second, it is possible that the number of bidders is misreported by homeowners. In this case, the coefficient on the number of bidders will also be biased downwards in magnitude. Third, while the data permit us to control for a rich set of differences in housing attributes and locations, the econometrician is unlikely to observe all housing characteristics that are observed by buyers and sellers. To the extent that houses with nice but unobserved features are both listed at a higher price and attract more bidders, this will introduce a bias into the estimated effect of the asking price. However, as shown by a structural analysis in Genesove and Han (2012b), the OLS estimator in this case would be biased downwards in magnitude in the manner of an error-in-variable bias. In other words, the actual role of the asking price in directing buyers' search should be even stronger.

To test whether unobserved housing characteristics indeed cause downward bias, we re-estimate our main specifications by including the tax assessment for the year of, or the year prior to listing. Taxes are a constant percentage of assessed value, and therefore serve as a perfect proxy for assessed value. Assessed value is typically based not only on housing attributes reported in the MLS database, but also on

[20] It is worth noting that there is a range of other sorts of search activity such as repeated visits to a house, home inspections, and time spent gathering and processing relevant information. It is not possible to consider these activities given available data.

the assessor's actual visit of the house and the neighborhood. Thus, assessed value contains more information about the house than is found in MLS data. For this reason, we add the property tax assessment value, along with dummies for the year of assessment, to control for part of unobserved house characteristics. Some observations lack tax information, and we drop them from the analysis.

The bottom panel of Table 5 presents the results of models with controls for taxes and tax years. Given the importance of home locations, we focus our discussion on the three columns where the district dummies are controlled for. Across these columns, the coefficient on the asking price remains significantly negative and becomes much larger in magnitude when taxes are included. In Column 6 where all the control variables are included, adding taxes almost doubles the magnitude of the directing effect of the asking price – lowering the asking price by 10% increases the number of bidders by 4%. In addition, the coefficient's precision is increased even further. Since taxes are used to control for part of unobserved housing characteristics, these results are consistent with what we expected from errors-in-variable bias as discussed earlier. Moreover, they suggest that our main results hold even after accounting for the spurious correlation between the asking price and the number of bidders induced by unobserved housing attributes. Note that since taxes cannot control for all unobserved housing attributes, we should treat the negative effect we found here as a lower bound for the true directing effect of the asking price.

It is well-known that home sellers sometimes revise their asking price. To consider this, in column 7, we repeat the specifications in column 6 but use the original asking price instead. We find that the effect of the original asking price on the number of bidders remains negative and statistically significant, although smaller than the effect of the final asking price. This is as expected, since what matters for buyer search is the asking price at the time of the visit and bidding decisions, not the original asking price. We will hereafter only use final asking price in the empirical specifications.

C. Alternate specifications

The discreteness of the number of bidders suggests that we can further explore the variation in relationship between the asking price and the bidding intensity. To this end, we begin by estimating a standard Probit model on the occurrence of multi-bidder sales, controlling for transaction period, district and housing attributes. In this model, the dependent variable is assigned a value of 1 if there are multiple bidders and 0 if there is one bidder. Table 6 reports the marginal effects of asking price. Other things being equal, reducing the asking price by 1 percent increases the probability of having multiple bidders by 1.23 percentage points. We then estimate an ordered Probit model where the number of bidders is regressed on the log of the asking price with usual controls. As shown in the bottom panel of Table 6, else equal, reducing the asking price by 1 percent increases the chance of having two bidders by 3.24 percentage points, the chance of having three bidders by 2.13 percentage points, the chance of having four bidders by 1.65

percentage points, and the chance of having five or more bidders by 1.99 percentage points. All estimates are statistically significant. While lowering asking price helps attract multiple bidders, attracting one additional bidder would require further reductions in the asking price. This is consistent with expectations.

The number of bidders is not only discrete but also over-dispersed, as shown in Figure 2. A legitimate concern is that the log-linear model, used in our main specifications, may fail to control for the over-dispersion in the number of bidders and therefore generate biased estimates. To address this concern, we estimate a negative binomial model where the number of bidders is again regressed on the log of asking price with a set of usual controls. The results are reported in Table 7. In column 1, we control for only transaction district and period. The coefficient on ln(Asking Price) is -0.27. In column 2, we add house attributes, and the magnitude of the coefficient almost doubles. In columns 3 and 4, we repeat the estimation in columns 1 and 2, but further include tax assessment as a control for the unobservable house attributes, the coefficient on ln(Asking Price) increases to -0.72 and -0.89 respectively. The estimates are statistically significant at the 1% level in all specifications. To interpret these coefficients, we further compute their incidence rates, which are reported in the bottom row. Take the estimates in column 4 as an example. For hedonically identical homes, increasing the asking price by 1 percent reduces the arrival rate of the potential bidders by 0.58 percentage points. These estimates provide strong evidence for the directing role of the asking price, even after accounting for the over-dispersion in the number of bidders. Note that the dispersion parameter is significantly positive in all specifications, suggesting that there is indeed more variation than if the process were Poisson.

D. Variation in the directing role of asking price

Another key prediction of our model is that the strength of the directing role of asking price varies depending on the state of the housing market and the degree of atypicality of houses. For example, in busts when there are fewer high-type buyers and when high-type buyers value a given house less, the directing effect of the asking price on buyers is stronger. In contrast, in booms when there are more high type buyers and higher type buyers valuing a given house more, a greater reduction in asking price is required to induce a given number of visits. On the other hand, the theoretical result on the atypicality effect is less clear. More atypical houses may strengthen the directing role of asking price, as buyers are less likely to find such houses as a good match and hence are less motivated to search. However, conditional on being matched with an atypical house in a good state, a buyer with particular taste might derive greater value from such a house. This would weaken the role of asking price as a commitment device. The net effect of atypicality on the directing role of asking price, thus, depends on which effect empirically dominates.

To test the model's implications regarding directed search in a bust, we consider the September, 2008– December, 2008 as a period of financial crisis, and use it as an empirical proxy for the bust period.

The sample period we analyze started with a boom market in 2006, followed by a slow and uncertain market trigged by the global financial crisis that began in September 2008. By early 2009, the housing market started rising again. To see this, we use the monthly median house price and monthly sales reported by the local real estate board and compute the year-to-year growth in deflated median house price and in sales for each month in the sample period.[21] As shown in Figure 3, the number of sales has been generally stable throughout 2006 and 2007. Then the sales started dropping in February 2008 (relative to the same month in the previous year) and continued to be around 20-25% off the previous year's through August 2008. In September 2008 the sales were about 6% less the previous year's, but then October's sales were about 63% of the previous year's. This continued until March 2009, after that the sales started increasing again. Turning to the median price, we find the real price stalled in September 2008 and then fell 11% in October 2008 (again compared to the same month in the previous year). The year-to-year price depreciation continued until June 2009, although at a much smaller magnitude. Together, the figure makes it clear that housing market in the sample metropolitan area was strong until 2007, followed by a significant bust triggered by the global financial crisis in Sept. 2008, and then a recovery in 2009. This justifies our choice of using September – December in 2008 "crisis" period to proxy for the housing market bust. It is worth noting, however, that the soft landing that this market experienced may mean that the results we obtain are weaker than they would be in a market that had a hard landing.

To test the effects of atypicality, we follow Haurin (1988) and Glower, Haurin, and Hendershott (1998). We create Haurin's atypicality measure in the following way.

$$ATYP_{ijt} = \Sigma_k \, |\exp(a+b_k h_{ik}) - \exp(a+b_k h_{jk}^*)| / SP_{ijt} \tag{VI.2}$$

where $ATYP_{ijt}$ and SP_{ijt} are the atypicality index and sales price for house *i* in district *j* at time *t*; h_{ik} is the kth physical attribute of house *i*; h_k^* is the mean value of the kth attribute of houses in district j in the year of transaction; a and b_k are the intercept and slope estimates from a hedonic regression using the overall market sample in the year when the property is transacted. This index should be interpreted as the aggregate value of deviation of a property's characteristics from the sample mean, weighted by the hedonic price of that characteristic.[22]

In Table 8, we expand the regressions in Table 5 by separately including the interaction of the asking price and the crisis period dummy as well as the interaction of the asking price with the atypicality

[21] In other words, the current month's data point is compared with the data point from the same month in the prior year. The growth rate is then calculated to get a comparative measure for how fast real price or the sales rose or fell over the 12-month period. This method reduces seasonal fluctuations and reveals the changes in market conditions.
[22] See Bar-Isaac et al (2015) for another application of Haurin's atypicality index.

index. Given that the atypicality index is constructed from a separate regression, the estimates of the asymptotic covariance matrix are corrected using the bootstrap strategy. Beginning with the top panel, the coefficient on asking price alone is positive when the district dummies are not included (Columns 1), but it becomes significantly negative once the district dummies are included (Columns 2-4). This is the same pattern that appeared in Table 4. More importantly, in Columns 2-4, the coefficients on the interaction variables are all negative and statistically significant, suggesting that there is significant variation in the directing role of asking price across different market segments and different house types.

In particular, in Column 4, where transaction period dummies, district dummies and housing attributes are all controlled for, the coefficient on the asking price is -0.24 (significant at the 1% level) and the coefficient on the interaction between asking price and the crisis dummy is -0.16 (significant at the 5% level). Together, these results indicate that lowering asking price by 10% would increase the number of bidders by 2.4% in normal times and by 4% in busts. These findings are consistent with cyclical variation in the directing role of the asking price predicted by the model.[23]

In the same column, we also find that the coefficient on the interaction between asking price and the atypicality index is -0.018 (significant at 1% level). This means that the effectiveness of the asking price in directing search strictly increases with the degree of house atypicality. In particular, lowing asking price 10% would increase the number of bidders by 7.8% for a house that is at the 10th percentile of the atypicality index (ATYP = 0.03); and 69% for a house that is at the 90the percentile of the atypicality index (ATYP = 0.37). This suggests that the marketing strategy of lowering asking price to attract bidders is much more effective for houses with more unusual features.

Turning to the bottom panel of Table 8, we find that our main results are again robust to the inclusion of taxes. In particular, the effect of the asking price alone on the number of bidders almost doubles in magnitude. Moreover, consistent with what we found before, this effect is strengthened in the housing market bust and for houses with more atypical features.

E. Empirical results: Transaction types

The model also has predictions about how housing transaction types – traditional, bidding war, or acceptance – will vary across the real estate cycle. An increase in the quality of a good match or a decrease in search costs will result in fewer traditional below-list sales and more bidding war sales. The model is

[23] Table C-1 in the online Appendix C provides a set of robustness checks where we interact the asking price with the year-to-year real house price appreciation and year-to-year changes in sales (both at the market level) rather than using the 2008 financial crisis period to proxy the bust. We find that an increase in the median real price or in the number of sales reduces the negative effect of the asking price on the number of bidders. The estimated relationship is strong and statistically significant. This provides reassuring evidence that the directing role of the asking price is strengthened in the housing market bust.

ambiguous in its predictions regarding the fraction of sales that involve the acceptance of the asking price, as discussed above. It is real estate agent folk wisdom that more sales above list are seen in a boom. While one would expect this outcome in a world where real estate booms and busts arose as unanticipated shocks, it is not completely obvious that this should be the case. The asking price is, after all, endogenous. The model's predictions are, nonetheless, consistent with the folk wisdom, and so when we test the former we are also assessing the latter. With regard to acceptance, we are not testing the model here but attempting to determine which of the theoretical possibilities is consistent with observation.

With that in mind, Columns 1-3 of Table 9 present results from regressing a set of dummy variables that indicate the incidence of traditional/bidding/acceptance-sales on the crisis proxy, an atypicality index, and a variety of control variables. Following the theoretical framework, we measure the instance of bidding by the fraction of above-list sales. In all specifications, we control for property characteristics, neighborhood conditions, and transaction period dummies. For traditional (below-list) sales, the coefficient on the financial crisis indicator is 1.90 and significant at the 1% level, indicating that for two hypothetically identical houses with average conditions, the predicted probability that a transaction occurs with a below-list price is 45% greater during the bust than in more normal circumstances. Turning to the above-list sales, the coefficient on the financial crisis indicator is -0.78 and significant at the 10% level, indicating that the predicted probability that a house ends up with an above-list price is 14% lower during a bust.[24] Together, these results are consistent with the model's predictions about the cyclical variations in the frequency of the traditional and bidding war sales, providing additional support for the directing role of the asking price in home sales.[25]

The model's predictions about the cyclical variations in acceptance rates are ambiguous. The middle column of Table 9 shows that the occurrence of acceptance sales is less likely in a bust than in a boom, although the relationship is statistically insignificant. Nevertheless, the pattern here is consistent with the descriptive evidence from the various surveys discussed above.

Finally, we find that the coefficients on the atypicality index are qualitatively similar to the estimates on the crisis dummy, although they are statistically insignificant in the case of traditional sales and acceptance sales. We previously discussed two ways that atypicality might impact transaction type. One was that atypical houses simply have fewer satisfactory matches (lower δ). The other was that atypical houses might also be better matches for households for which the house is a good fit (higher x_H). The results seem to suggest that the former effect is stronger. An atypical house experiences a market similar to an

---

[24]These results become slight stronger both economically and statistically in a Probit model regressing a dummy for sales with multiple bidders on our control variables.

[25]The results are also consistent with the wealth effects documented in Genesove and Mayer (1997) and the loss aversion behavior as emphasized in Genesove and Mayer (2001).

ordinary house in a bust in this regard. There are fewer bidding wars. This result is related to the finding of Liu et al (2014) that there were fewer above-list sales in Phoenix for the largest houses since these large houses are atypical by the Haurin measure.

VII. Conclusions

This paper has considered, both theoretically and empirically, the role of the asking price in housing transactions. The motivation is that houses sell for less than asking price and for more than asking price. This suggests that asking price might not matter. However, a nontrivial share of housing transactions also involve a price equal to asking price, which would not be likely if housing transactions were simply auctions, with asking price simply serving as an empty description of the house.

To resolve this puzzle, the paper proposes a search model where asking price is a commitment when at most one buyer has a match value that is equal to or greater. The model shows how asking price can direct search. A lower asking price encourages more potential buyers to visit, but only up to a point. Past this bound, a lower asking price leads to more bidding wars, and buyer recognition of this means that more cannot be encouraged to search. This means that although asking price can be a useful strategic instrument for home sellers, there is a limit to the search that can be encouraged.

The paper carries out a number of empirical tests of the model's predictions. We show that there are nontrivial fractions of sales that are below-list, above-list, and at-list, as the model predicts. We show that asking price is negatively related to the number of bidders, a proxy for buyer search activity. We also show that this relationship is stronger in a bust than in a boom and also stronger for an atypical house. Finally, we show that the share of below-list sales falls in a boom, while the shares of at-list and above-list sales rise. The latter results are consistent with real estate agent folk wisdom.

It goes without saying that there are other aspects of asking price that the paper has not considered. Behavioral aspects of housing transactions are perhaps the most important of these. First, an asking price is one of the first pieces of information that a homebuyer obtains about a house. Bucchianeri and Minson (2013) present evidence consistent with a "framing" role for asking price, where setting a high asking price impact buyer evaluations of match quality. Second, especially in boom markets, housing transactions can become heated, and it is not difficult to believe that emotion plays a role. Piazzesi and Schneider (2009) show that in a search market, a small number of optimistic investors can have large effects on house prices even if they buy only a small fraction of houses. In a setting of online auctions, Lee and Malmendier (2010) have shown that bidders sometimes pay more in a competitive auction than a price at for which the object is offered in an ordinary sale on the same webpage. This seems to suggest that housing transactions have the potential for the same sort of emotional bidding. To the extent that asking price encourages search, it is possible that it may create such a situation, to the benefit of the seller. Third, Genesove and Mayer (2001) present evidence consistent with loss aversion in housing markets. This will impact a seller's entire marketing strategy, including the setting of asking price. While we see these behavioral phenomena as being worth consideration, we also believe that it is important to see how far a conventional microeconomic model can go in explaining observed data. We believe that this paper's demonstration that asking price can direct search when it is neither ceiling nor posted price is a useful step in doing so.

References

Abel, J.R. and R. Dietz, 2010. Bypassing the Bust: The Stability of Upstate New York's Housing Markets During the Recession. Federal Reserve Bank of New York, *Current Issues in Economics and Finance* 16, 1-9.

Albrecht, J., Gautier, P., and Vroman, S., 2014. Directed search in the housing market. Working paper, Georgetown University.

Anglin, P., Rutherford, R., & Springer, T., 2003. The trade-off between the selling price of residential properties and time-on-the-market: The impact of price setting. *Journal of Real Estate Finance and Economics* 26, 95-111.

Arnold, M. A., 1999. Search, bargaining and optimal asking prices. *Real Estate Economics* 27, 453-481.

Bar-Isaac, H. and A. Gavazza , 2015. Brokers' contractual arrangements in the Manhattan residential rental market, *Journal of Urban Economics* 86, 73-82.

Barta, P., 2003. How to set a price for your house, *Wall Street Journal*, May 23, http://www.wsj.com/articles/SB121380010708384369.

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

Carrillo, P.E., 2012. An empirical stationary equilibrium search model of the housing market. *International Economic Review* 53, 203-234.

Carrillo, P.E., 2013. To sell or not to sell: Measuring the heat of the housing market." *Real Estate Economics* 41, 310-346.

Carrillo, P.E., E. R. de Wit, W. Larson, 2015. Can tightness in the housing market help predict subsequent home price appreciation? Evidence from the U.S. and the Netherlands. *Real Estate Economics* 43, 609-651.

Case, K. and Shiller, R., 1988. The behavior of home buyers in boom and post-boom markets. *New England Economic Review* 11, 29-46.

Case, K. and Shiller, R., 2003. Is there a bubble in the housing market? *Brookings Papers on Economic Activity* 2, 299-342.

Chen, Y. and Rosenthal, R. W., 1996a. On the use of ceiling-price commitments by monopolists. *The RAND Journal of Economics* 27, 207-220.

Chen, Y. and Rosenthal, R. W., 1996b. Asking prices as commitment devices. *International Economic Review* 37, 129-155.

Frey, B.S. and W.W. Pommerehne, 1993. On the fairness of pricing – An empirical survey among the general population, *Journal of Economic Behavior and Organization* 20, 295-307.

Genesove, D. and Han L., 2012a. Search and matching in the housing market. *Journal of Urban Economics* 72, 31-45.

Genesove, D. and Han L., 2012b. Measuring the thinness of real estate markets. Working Paper, University of Toronto.

Genesove, D. and Mayer, C., 1997. Equity and time to sale in the real estate market. *American Economic Review* 87(3), 255-269.

Genesove, D. and Mayer, C., 2001. Loss aversion and seller behavior: Evidence from housing markets. *Quarterly Journal of Economics* 116, 1233-1260.

Gerardi, K., E. Rosenblatt, P.S. Willen, and V. Yao, 2015. Foreclosure externalities: New evidence," *Journal of Urban Economics* 87, 42-56.

Glower, M. Haurin, D., and Hendershott, P., 1998. Selling time and selling price: The influence of seller motivation. *Real Estate Economics* 26, 719-740.

Green, R.K., and K.D. Vandell, 1998. Optimal Asking Price and Bid Acceptance Strategies for Residential Sales, Working Paper, University of Wisconsin.

Han, L. and Strange W., 2014. Bidding wars for houses. *Real Estate Economics*, 42, 1-32.

Han, L. and Strange W. , 2015. The microstructure of housing markets: Search, bargaining, and brokerage, in *Handbook of Regional and Urban Economics, Volume 5B*, G. Duranton, J.V. Henderson, and W. Strange (eds.), Amsterdam: Elsevier, 813-886.

Haurin, D., 1988. The duration of marketing time of residential housing. *Real Estate Economics* 16, 396-410.

Haurin, D. R., Haurin, J. L., Nadauld, T. and Sanders, A. B. 2010. List prices, sale prices, and marketing time: An application to U.S. housing markets. *Real Estate Economics* 38, 659-685.

Hoyt, W. H. and S.S. Rosenthal, 1990. Capital gains taxation and the demand for owner-occupied housing. *Review of Economics and Statistics* 72, 45-54.

Knight, J. R., 2002. Listing price, time on market, and ultimate selling price: Causes and effects of listing price changes. *Real Estate Economics* 30, 213-237.

Lambie-Hanson, L., 2015. When does delinquency result in neglect? Mortgage distress and property maintenance, *Journal of Urban Economics* 90, 1-16.

Lee, Y.H. and Malmendier, U. 2011. The bidder's curse. *American Economic Review* 101, 749-787.

Liu, C. H., A. Nowak, A., and S. Rosenthal, 2014. Bubbles, post-crash dynamics, and the housing market. Working Paper, Syracuse University.

Merlo, A. and Ortalo-Magne, F., 2004. Bargaining over residential real estate: evidence from England. *Journal of Urban Economics* 56, 192-216.

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

Novy-Marx, R., 2009. Hot and cold markets. *Real Estate Economics* 37, 1-22.

Peters, M., 1991. Ex ante price offers in matching games non-steady states. *Econometrica* 59, 1425-1454.

Piazzesi, M. and M. Schneider, 2009. Momentum traders in the housing market: Survey evidence and a search model. *American Economic Review: Papers & Proceedings* 2, 406-411.

Salant, S. W., 1991. For sale by owner: When to use a broker and how to price the house. *Journal of Real Estate Finance and Economics* 4, 157-74.

Sass, T. R., 1988. A note on optimal price cutting behavior under demand uncertainty. *The Review of Economics and Statistics* 70, 336-339.

Stull, W. J., 1978. The landlord's dilemma: Asking rent strategies in a heterogeneous housing market. *Journal of Urban Economics* 5, 101-115.

Tracy, J. and H. Schneider, 2001. Stocks in the household portfolio: A look back at the 1990s, *Current Issues in Economics and Finance* 7, 1-6.

Yavas, A. and Yang, S., 1995. The strategic role of listing price in marketing real estate: Theory and evidence. *Real Estate Economics* 23, 347-368.

Yinger, J. 1981. A search model of real estate broker behavior. *American Economic Review* 71, 591-605.

Zuehlke, T. W., 1987. Duration dependence in the housing market. *The Review of Economics and Statistics* 69, 701-709.

Table 1: Below-, At-, and Above-List Sales in Four Cities:
Evidence from Case and Shiller (1988, 2003)

	Los Angeles		San Francisco		Boston		Milwaukee		Average	
	1988	2003	1988	2003	1988	2003	1988	2003	1988	2003
Sale Price < List Price	6.3	19.9	9.8	45.8	10.5	21.3	3.3	17.5	4.9	25.5
Sale Price = List Price	38.0	50.4	26.8	27.5	23.5	59.1	22.7	52.4	27.9	48.4
Sale Price > List Price	55.7	29.7	63.4	26.7	76.0	28.6	74.0	31.1	67.1	29.1
# responses	237	141	194	153	200	203	242	183	873	680

Note: This table reproduces the statistics from Case and Shiller (1988, 2003).

Table 2: Below-, At-, and Above-List Sales: NAR Evidence

	Aggregate Sample			Buyer Sample			Seller Sample		
	Average Sale/List Ratio	Fraction of Below List Sales	Fraction of Sales at List Price	Average Sale/List Ratio	Fraction of Below List Sales	Fraction of Sales at List Price	Average Sale/List Ratio	Fraction of Below List Sales	Fraction of Sales at List Price
2003-2006	97.76% (33,188)	57.08% (33,188)	29.43% (33,188)	97.79% (23,585)	54.88% (23,585)	31.29% (23,585)	97.71% (9,603)	62.47% (9,603)	24.86% (9,603)
2007-2010	94.82% (40,288)	74.29% (40,288)	17.48% (40,288)	94.93% (31,547)	72.81% (31,547)	18.29% (31,547)	94.42% (8,741)	79.61% (8,741)	14.55% (8,741)

Note: The data source is the National Association of Realtors homebuyer and seller surveys (2003-2010). The sample excludes properties sold through foreclosures. Number of observations is reported in parentheses.

Table 3: Descriptive Statistics

Variables	Mean	S.D.
Number of bidders	1.73	1.75
Sale price	$ 416,154.2	$ 208,774.2
Final Asking Price	$ 422,742.2	$ 210,894.7
Original Asking price	$ 425,764.6	$ 212,076.1
# of bedrooms	3.31	0.67
# of washrooms	2.80	0.92
Lot front (feet)	41.75	68.51
Lot depth (feet)	120.59	112.56
Primary Room length (feet)	15.49	6.11
Primary Room width (feet)	11.73	18.90
Garage space	1.26	0.77
Property Tax Assessment	$3,154.36	$1,508.22
Period covered	Jan. 2006-Dec. 2009	

Note: This table reports summary statistics of the raw variables. Number of bidders is reported by buyers who responded to the survey, and other variables are reported by the local MLS. Sale price and asking price are measured in 2000 dollars.

Table 4a: Below-, At-, and Above-List Sales By Year

	Sales/List Ratio	Below List (%)	At List (%)	Above List (%)	# Responses	Mean Price (MLS)	Sales Volume (MLS)	% Multiple Bidders	# of Bidder responses
2006	97.88%	75.90%	9.92%	14.19%	585	384,100.4	23,204	35.45%	663
2007	98.22%	72.39%	7.82%	19.78%	652	411,444.2	25,751	38.24%	740
2008	97.45%	83.61%	5.46%	10.93%	1025	417,337.6	19,562	29.55%	1154
2009	97.03%	81.02%	8.37%	10.61%	490	426,961.7	23,367	37.21%	524

Note: The statistics are computed based on the Genesove-Han Survey.

Table 4b: Bidding Statistics for Below-, At-, and Above-List Sales

	Days On Market		Number of Bidders		% Multiple Bidders	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Sales Price < List Price	30.46	29.10	1.38	0.99	21.61%	41.17%
Sales Price = List Price	19.87	20.34	1.84	1.31	47.57%	50.08%
Sales Price > List Price	11.03	11.81	3.80	3.28	88.55%	31.88%

Note: The statistics are computed based on the Genesove-Han Survey. List price refers to final asking price that is posted to attract visitors.

Table 5: Bidder Response to Asking Price

Dependent Variable	Ln(Number of Bidders)						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Without controls for property tax assessment						
ln(Final Ask Price)	0.08	0.09	0.14	-0.14	-0.12	-0.22	
	(1.85)	(1.97)	(2.98)	(-4.21)	(-4.00)	(-4.44)	
ln(Original Ask Price)							-0.17
							(-3.59)
Period	No	44	44	No	44	44	44
district	No	No	No	25	25	25	25
House Attributes	No	No	Yes	No	No	Yes	Yes
Property Tax Assessment	No	No	No	No	No	No	No
Obs.	2947	2947	2891	2947	2947	2891	2891
	With controls for property tax assessment						
ln(Final Ask Price)	0.20	0.20	0.12	-0.36	-0.33	-0.40	
	(4.20)	(4.23)	(2.34)	(-4.48)	(-4.14)	(-5.19)	
ln(Original Ask Price)							-0.23
							(-2.38)
Period	No	44	44	No	44	44	44
district	No	No	No	25	25	25	25
House Attributes	No	No	Yes	No	No	Yes	Yes
Property Tax Assessment	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2708	2708	2667	2708	2708	2667	2667

Note: This table reports estimates from the log-linear regressions of the number of bidders on the list price, with a variety of controls. Standard errors are clustered at the district level. T-statistics are reported in parentheses. The number of bidders is reported by buyers, and other variables are reported by the MLS. The top panel excludes property tax and dummy indicators for tax assessment year, while the bottom panel includes them. The asking price is measured by the final asking price in columns 1-6, and by the original ask price in column 7. House attributes include dummies for the number of bedrooms interacted with dummies for the number of washrooms, lot front, lot depth, the length and width of the primary room, dummy variables for basement, garage space and occupancy.

Table 6: Marginal Effects from Probit Models

	Standard Probit	
	dPr(N>1)/dln(Final Asking Price)	t-stat
N > 1	-0.123	-4.16
	Ordered Probit	
# Bidders	dN/dln(Final Asking Price)	t-stat
N = 2	-0.0324	-3.52
N = 3	-0.0213	-3.55
ie = 4	-0.0165	-3.39
N ≥ 5	-0.0199	-3.75

Note: The dependent variable is a dummy variable that indicates multiple bidders (N>1) in the top panel, and the number of bidders (N) in the bottom panel. In both cases, the key variable of interest is the log of final asking price (ln(Asking Price)). Controls include transaction period, district, as well as housing attributes as described in the note to Table 5. Standard errors are clustered at the district level. For the ease of interpretation, the estimates reported here are marginal effects computed based on the raw Probit coefficients.

Table 7: A Negative Binomial Model

Dependent Variables	Number of Bidders (1)	(2)	(3)	(4)
Ln(Final Asking Price)	-0.2733	-0.4986	-0.7208	-0.8851
	(-4.30)	(-4.02)	(-4.13)	(-4.47)
Dispersion	0.0810	0.0728	0.0781	0.0694
	(2.67)	(2.69)	(2.77)	(2.75)
Period	44	44	44	44
district	25	25	25	25
House Attributes	No	Yes	Yes	No
Property Tax Assessment	No	No	Yes	Yes
Obs.	2947	2891	2708	2667
IRR of ln(Final Asking Price)	0.7609	0.6074	0.4866	0.4127

Note: This table reports estimates from the negative binomial regressions of the number of bidders on the log of asking price, with a variety of controls. Standard errors are clustered at the district level. T-stats are reported in parentheses. The incidence rate ratio (IRR) of ln(Final Asking Price) is reported at the bottom row. House attributes are described in the note to Table 5. Property tax assessment controls include both property taxes and dummy indicators for the year of tax assessment.

Table 8: Variation in Bidder Response to Asking Price: Bust and Atypicality

Dependent Variable	Ln(Number of Bidders) (1)	(2)	(3)	(4)
	Without controls for property tax assessment			
Ln(Asking Price)	0.08	-0.137	-0.109	-0.24
	(3.09)	(-3.61)	(-2.56)	(-4.22)
Ln(Asking Price)*Atypicality	-0.008	-0.011	-0.011	-0.018
	(-1.43)	(-2.16)	(-1.77)	(-3.22)
Ln(Asking Price)*Crisis	-0.009	-0.009	-0.14	-0.16
	(-4.13)	(-4.23)	(-2.25)	(-2.54)
Period	No	No	44	44
district	No	25	25	25
House Attributes	No	No	No	Yes
Property Tax Assessment	No	No	No	No
Obs.	2891	2891	2891	2891
	Without controls for property tax assessment			
Ln(Asking Price)	0.20	-0.38	-0.33	-0.40
	(5.85)	(-4.20)	(-4.78)	(-4.95)
Ln(Asking Price)*Atypicality	-0.010	-0.011	-0.011	-0.016
	(-2.00)	(-2.22)	(-2.01)	(-3.24)
Ln(Asking Price)*Crisis	-0.008	-0.008	-0.10	-0.12
	(-3.37)	(-3.49)	(-1.71)	(-1.65)
Period	No	No	44	44
district	No	25	25	25
House Attributes	No	No	No	Yes
Property Tax Assessment	Yes	Yes	Yes	Yes
Obs.	2667	2667	2667	2667

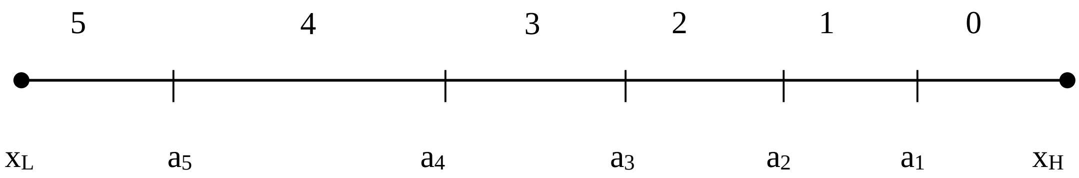
Note: This table reports estimates from the log-linear regressions of the number of bidders on the asking price, with a variety of controls. Asking price here refers to the final asking price. Standard errors are bootstrapped. T-statistics are reported in parentheses. The number of bidders is reported by buyers, and other variables are reported by the MLS. The atypicality index is constructed to measure the degree of unusual features of a property based on Haurin (1988). Crisis is a dummy variable that equals 1 if transaction occurs during September, 2008– December, 2008. The top panel excludes property tax and dummy indicators for the tax assessment year, while the bottom panel includes them.

Table 9: Variation in the Nature of Sales: Bust and Atypicality

Dependent Variable	Traditional Sales Indicator (Sale Price < List Price)	Acceptance Sales Indicator (Sale Price = List Price)	Above-Listing Sales Indicator (Sale Price > List Price)
Crisis	1.89 (5.85)	-1.68 (-1.26)	-0.78 (-1.93)
Atypicality	0.20 (0.45)	0.12 (0.52)	-0.39 (-2.35)
Period	44	44	44
District	25	25	25
House Attributes	Yes	Yes	Yes
Obs.	2505	2505	2505

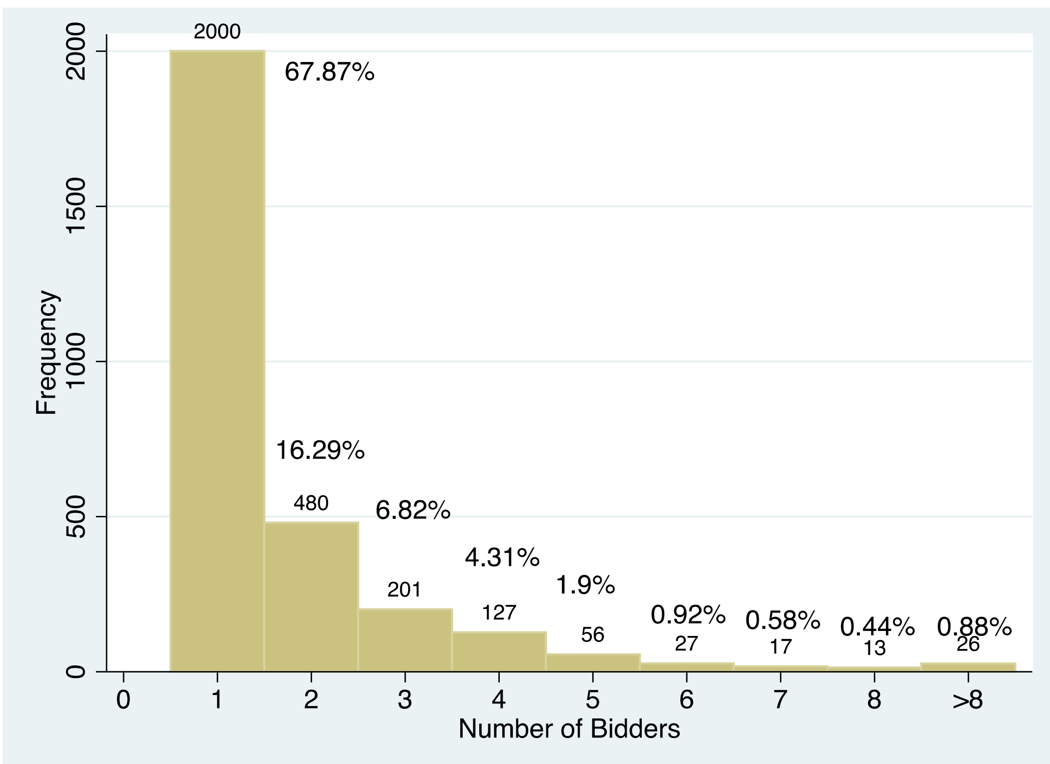
Note: This table reports estimates from the Probit regressions of transaction type on market crisis indicator and property atypicality index, with a variety of controls. The atypicality index is constructed to measure the degree of unusual features of a property based on Haurin (1988). Crisis is a dummy variable that equals 1 if transaction occurs during September, 2008– December, 2008. Standard errors are bootstrapped. T-statistics are reported in parentheses. The indicators of below-, at-, and above-list sales are based on buyers' reports, and other variables are reported by the MLS. House attributes are described in the note to Table 5.

Figure 1. Asking price and search



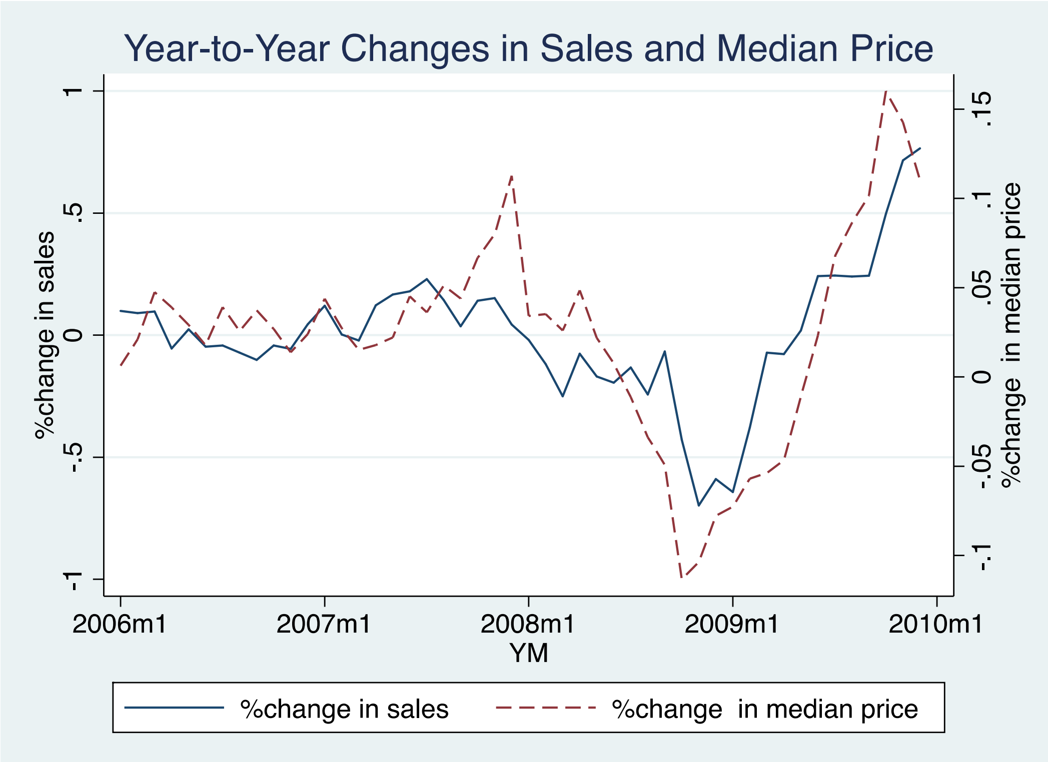
Note: the figure shows how asking prices between x_L and x_H impact the number of visitors to a house. When $a > a_1$, no buyer visits. Above a_2 up to a_1, 1 buyer visits, and so on.

Figure 2: Histogram of the Number of Bidders



Data source: Homebuyer survey conducted by Han and Genesove (2012b).

Figure 3: Year-to-Year Changes in Sales and Median Price



Note: We use the monthly median house price and number of sales reported by the local real estate board and compute the year-to-year growth in deflated median price and sales for each month in the sample metropolitan area.

Online Appendix A. Continuous Model

This Appendix considers an alternate model of the role of asking price. The specification is as in the paper with one difference. Instead of buyer valuations being binomial draws from the two point support $\{x_L, x_H\}$, we now suppose that the valuation after the visit is a draw from a continuous probability distribution on $[x_L, x_H]$. Let f(x) and F(x) denote, respectively, the ordinary pdf. and cdf. This Appendix will show that key results from the discrete model continue to hold and that there are some additional forces at work that this alternate model allows us to explore.

To begin considering this setup, suppose that n = 1, so there is only one visitor and suppose that $a \in (x_L, x_H)$. As in the paper, price is given by a bargain between seller and buyer, with

$$p = \theta x + (1-\theta)x_L. \tag{A.1}$$

Again, as in the paper, if $p \geq a$, then the buyer would choose to accept since this gives a lower price than does negotiation. Otherwise, the sale will be traditional with sales price less than asking price.

These two cases are illustrated in the two panels of Figure A1. Panel (a) shows how different draws of buyer valuation x correspond to different transaction types taking asking price as given. The one visitor would accept the asking price only if the valuation is large enough that the negotiated price would be greater than asking price. Using (A.1), the critical value is $x_a = 1/\theta * (a - (1-\theta)x_L)$. For $x \leq x_a$, the sale would proceed as a traditional below-list sale. Panel (b) tells a similar story with a focus on asking price taking x as given. For a given valuation, asking price must be low enough that accepting it is preferred by the buyer to negotiation. For given x, the critical asking price is given by $a_\theta = \theta x + (1-\theta)x_L$.

With n = 1, the expected utility of the visitor is

$$\begin{aligned} v_1 &= \int_{xL}^{xa} (x - p(x)) f(x)dx + \int_{xa}^{xH} (x - a) f(x)dx - c \\ &= E(x) - c - \alpha a - (1-\alpha)[\theta E(x|x<x_a) + (1-\theta)x_L] \end{aligned} \tag{A.2}$$

In order to consider search in this situation, we require assumptions that are parallel to Assumptions 1-3 from the body of the paper. (weak bargaining power, potentially valuable search, and potentially valuable transaction). There is weak bargaining power if

$$\text{Assumption 1}'\text{:}\quad (1-\theta)(E(x)-x_L) \leq c \tag{A.3}$$

We suppose that Assumption 1′ holds, ensuring that at a = x_H, n = 0. There is potentially valuable search if

$$\text{Assumption 2}': \; E(x) - c - x_L \geq 0. \tag{A.4}$$

We suppose that Assumption 2′ holds also. In this setup, at a = x_L, we have

$$\nu_1 = E(x) - c - x_L \geq 0, \tag{A.5}$$

by potentially valuable search. Since $\nu_1 \leq 0$ at a = x_H and ν_1 is monotonically decreasing in asking price for fixed n, there exists a unique a_1 such that $\nu_1 = 0$. There is a potentially valuable transaction if

$$\text{Assumption 3}': \; E(x) - c - s - x_L \geq 0 \tag{A.6}$$

We suppose Assumption 3′ holds.

Seller expected profit with n = 1 is given by

$$\begin{aligned}\pi_1 &= \int_{xL}^{xa} p(x) f(x) dx + \int_{xa}^{xH} af(x) dx - x_L - s \\ &= (1-\alpha)[\theta E(x|x<x_a) + (1-\theta) x_L] + \alpha a - x_L - s.\end{aligned} \tag{A.7}$$

At a = a_1,

$$\pi_1 = E(x) - c - s - x_L \geq 0 \text{ (A.8)}$$

by the potentially valuable transaction assumption.

All of this together means that with weak bargaining power, potentially valuable search, and potentially valuable transactions, the seller has an incentive to use asking price to direct search. Setting an asking price at $a_1 < x_H$ and attracting one visitor gives positive profit and so dominates setting a = x_H.

Now, suppose that there are $n \geq 2$ visitors. In this case, further notation is required. Let $x_{(i)}$ denote the i^{th} order statistic of a sample of n draws from this distribution, with $x_{(1)}$ denoting the largest value. Let $h(x_{(1)}, x_{(2)},\ldots,x_{(n)})$ and $H(x_{(1)}, x_{(2)},\ldots,x_{(n)})$ denote the associated joint pdf and cdf of the order statistics. Let $h_{(i)}(x_{(i)})$ and $H_{(i)}(x_{(i)})$ denote the pdf of the i^{th} order statistic, while $h_{(ij)}(x_{(i)}, x_{(j)})$ and $H_{(ij)}(x_{(i)}, x_{(j)})$ denote the joint pdf and cdf of the i^{th} and j^{th} order statistics, with i < j. We will make most use of $h_{(12)}(x_{(1)}, x_{(2)})$ and

$H_{(12)}(x_{(1)}, x_{(2)})$, the joint pdf and cdf of the first and second order statistics.

With $n \geq 2$, there are now three possibilities for transaction type: acceptance, traditional, and now bidding war. In this case, in the absence of an asking price, with highest and second highest valuations given by $x_{(1)}$ and $x_{(2)}$, negotiation produces a sales price of

$$p = \theta\, x_{(1)} + (1-\theta)x_{(2)}. \tag{A.9}$$

Suppose that $p \leq a$. In this case, asking price is irrelevant. When asking price is high relative to the sales price that would have emerged from negotiation, then asking price plays no role in the transaction. This is the traditional case. Suppose instead that $p \geq a$. In this case, it is possible but not certain that asking price matters. If $x_{(2)} < a$, only the highest valuation buyer with match value equal to $x_{(1)}$ is willing to pay the asking price. This is the acceptance case, with sales price equal to asking price. If instead $x_{(2)} \geq a$, there are two or more buyers willing to buy the house at the asking price. In this case, there will be a bidding war and sales price will equal p.

The three types of transaction are illustrated in Figures A2. Panel (a) shows how transaction type depends on $x_{(2)}$ for fixed a and $x_{(1)}$. In this panel, we show only the case where $a > x_{(1)}$, since $a < x_{(1)}$ removes the possibility of a bidding war. In the panel, if $x_{(2)}$ is small, less than

$$x_{(2),a} = (1/(1-\theta))(a-\theta x_{(1)}), \tag{A.10}$$

then the transaction takes the traditional form. For intermediate values of $x_{(2)}$, between $x_{(2),a}$ and a, the transaction involves acceptance. For high values, $x_{(2)} > a$, the transaction takes the form of a bidding war. Panel (b) shows how transaction type depends on asking price for given realizations of $x_{(1)}$ and $x_{(2)}$. A low asking price leads to a bidding war, while a high asking price, greater than $a_\theta = \theta x_{(1)} + (1-\theta)x_{(2)}$ produces a traditional sale. An intermediate asking price, between $x_{(2)}$ and a_θ, gives acceptance.

Transaction type thus depends on asking price and the realization of the highest and second-highest valuations as depicted in Figure A3. The probabilities of the three cases depend on the distribution of the order statistics. A traditional sale occurs when $(x_{(1)},x_{(2)}) \in T = \{(x_{(1)},x_{(2)}) |\ \theta\, x_{(1)} + (1-\theta)x_{(2)} \leq a\}$. An acceptance occurs when $(x_{(1)},x_{(2)}) \in A = \{(x_{(1)},x_{(2)}) |\ x_{(2)} \leq a \text{ and } \theta\, x_{(1)} + (1-\theta)x_{(2)} \geq a\}$. A bidding war occurs when $(x_{(1)},x_{(2)}) \in B = \{(x_{(1)},x_{(2)}) |\ x_{(2)} \geq a\}$. The probabilities of these are, respectively, $\tau = \iint_T h_{(12)}(x_{(1)}, x_{(2)})dx_{(1)}dx_{(2)}$, $\alpha = \iint_A h_{(12)}(x_{(1)}, x_{(2)})dx_{(1)}dx_{(2)}$, and $\beta = \iint_B h_{(12)}(x_{(1)}, x_{(2)})dx_{(1)}dx_{(2)} = \int_a^{x_H} h_{(2)}(x_{(2)})dx_{(2)}$, where $h_{(2)}(\cdot)$ is the marginal pdf of the second order statistic.

Even when x has a convenient distribution such as the uniform, order statistics are intractable for general n, but they do allow computation of numerical solutions. In the case of a uniform x, the order statistics are from the family of beta distributions. For $n \geq 2$, the first order statistic $x_{(1)}$ – the highest value in our notation -- has the pdf

$$h_{(1)}(x_{(1)}) = n\,[(x_{(1)}-x_L)/(x_H-x_L)]^{n-1}[1/(x_H-x_L)], \tag{A.11}$$

while the second order statistic has pdf

$$h_{(2)}(x_{(2)}) = n(n-1)\,[(x_{(2)}-x_L)/(x_H-x_L)]^{n-2}[(x_H-x_{(2)})/(x_H-x_L)][1/(x_H-x_L)]. \tag{A.12}$$

The joint pdf of the first and second order statistics is

$$h_{(12)}(x_{(1)}, x_{(2)}) = n(n-1)\,[(x_{(2)}-x_L)/(x_H-x_L)]^{n-2}[1/(x_H-x_L)]^2 \tag{A.13}$$

These can be used to generate probabilities and expected payoffs for numerical computation.

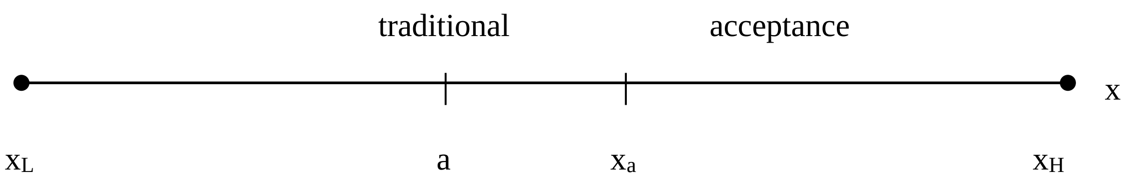
Despite the intractability, one can show that the key results from the discrete case continue to hold. The existence of three types of housing sale (Proposition 1) has already been established. It has also been established that the seller will use asking price to direct search at least by setting it below x_H and encouraging one visitor. We now consider the possibility of having more than one visitor.

Beginning with one visitor, there are two possible cases, acceptance and traditional. These two cases can be seen in Panel (a) of Figure 1 or along the horizontal axis in Figure 3. Adding another visitor moves us to a two dimensional case, as in the entirety of Figure 3. The effect on expected utility depends on the specific realizations of x for the two visitors. Suppose that $x_2 < x_1$. Suppose that x_1 is large but x_2 is small as in region z_1. In this case, the payoff to the highest-value visitor does not depend at all on the additional low-value visitor. In every other case, the payoff to the highest-value visitor falls. In region z_2 (high x_1 and x_2), there is now a bidding war, which by construction gives lower payoff. In region z_3 (moderate x_1 and x_2), there is also a bidding war, which is worse for visitor-1 than in the absence of the second visit. In region z_4 (moderate x_1 and somewhat lower x_2), the high-value visitor now accepts when he/she would not have in the absence of the other visitor. In regions z_5 and z_6, the high-value visitor is worse off since the presence of the second visitor results in a higher price under the traditional regime. In sum, adding a visitor reduces utility even if the second visitor has lower valuation. And adding a visitor also introduces the *ex ante* possibility that one is not the highest type, further reducing utility. This means that at a_1, where expected utility is exactly equal to zero with one visitor, expected utility is strictly negative with two visitors. This means that an asking price low enough to induce two visitors to search, a_2, if it exists must be lower than a_1.A similar argument can be used to show that a_{n+1}, if it exists, is lower than a_n. This gives something resembling the monotonic search-directing relationship between asking price and search that we obtained in the discrete model.

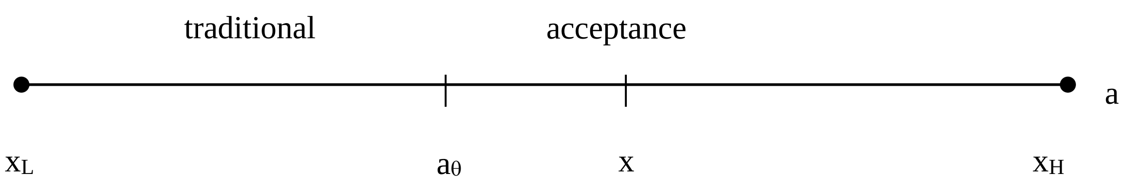
There is an important difference in this continuous model. In the discrete model, a very low asking price made search attractive even with multiple searchers, since it is possible that one visitor draws x_H and the rest draw x_L. In the continuous model, this is not the case. Setting a = x_L induces only one visitor. If, in contrast, n =2, there is a bidding war for sure, which means that the expected utility of the second search is negative. By continuity, there exists an asking price a_2' such that when asking price equals a_2', the expected utility of the second search is exactly zero. Similarly, for a_3', and so on. This means that the demand relationship in the continuous model is non-monotonic, a consequence of the possibility of bidding wars. Beyond a critical level of asking price, reductions no longer encourage visits. A similar result obtained in the discrete model, with the difference being that the critical level is in the interior of [x_L, x_H] in the continuous model.

Figure A1. Acceptance and traditional cases with n=1

Panel (a): As a function of valuation.



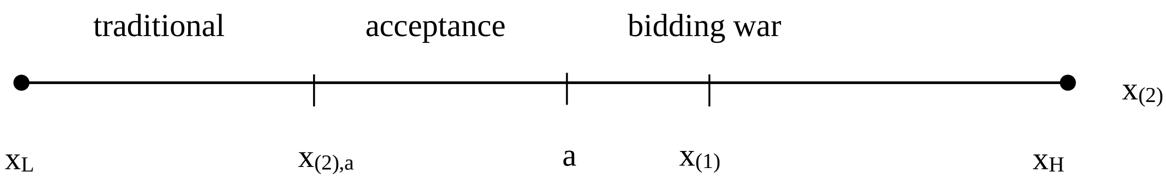
Panel (b): As a function of asking price.



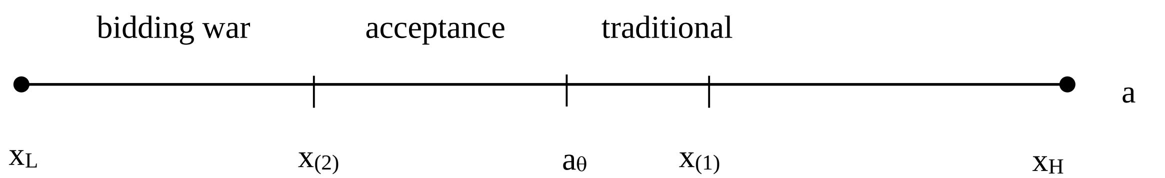
Note: This figure shows how asking price and valuation interact to determine transaction type when there is one visitor. Taking asking price as given, panel (a) maps values of x into the two possible sales cases, traditional below list sale and acceptance of the asking price. Taking x as given, panel (b) maps values of asking price into the same two possible sales cases.

Figure A2. Transaction type with n=2.

Panel (a): As a function of second highest valuation, $x_{(2)}$, when $x_{(1)} > a$.

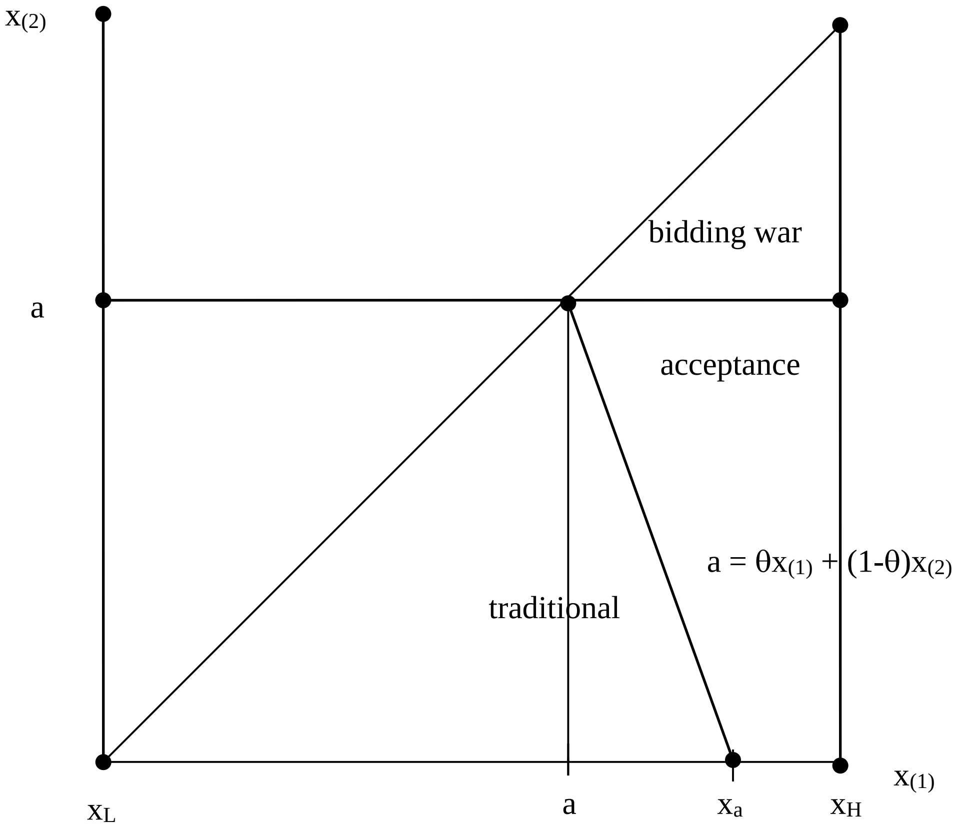


Panel (b): As a function of asking price, a.



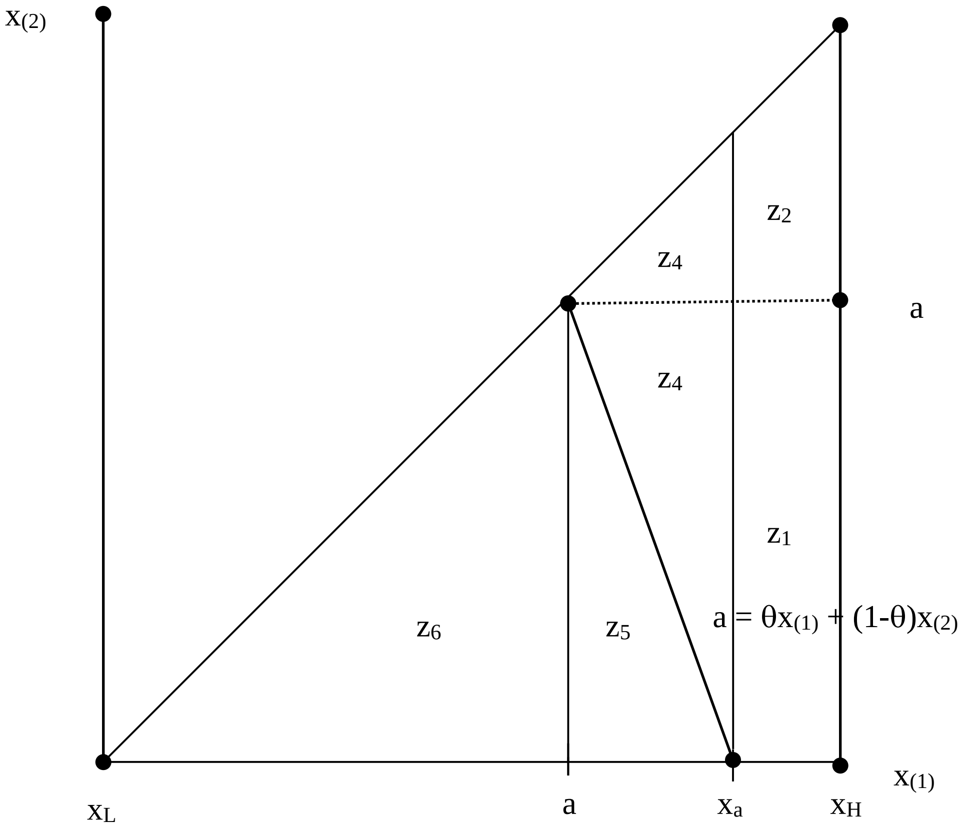
Note: This figure shows how asking price and valuation interact to determine transaction type with more than one visitor. Taking asking price and $x_{(1)}$ as given, panel (a) maps values of $x_{(2)}$ into the three possible sales cases, traditional below list sale, acceptance of the asking price, and above list bidding war. It considers the case where $x_{(1)} > a$, since otherwise a bidding war is not possible. Taking $x_{(1)}$ and $x_{(2)}$ as given, panel (b) maps values of asking price into the same three possible sales cases.

Figure A3. Acceptance, bidding war, and traditional cases with n=2 as they relate to $x_{(1)}$ and $x_{(2)}$.



Note: For the continuous model, the figure maps values of $x_{(1)}$ and $x_{(2)}$ into the three possible cases.

Figure A4. The effect of adding another visitor.



Note: For the continuous model, the figure maps values of $x_{(1)}$ and $x_{(2)}$ into the three possible cases.

Online Appendix B. Simulations

This Appendix presents some numerical simulations that illuminate some of the key features of the paper's model of asking price. Table B-1 presents the demand schedule for various conceptions of boom and bust. The first column gives a base case example. In it, we normalize $x_L = 0$ and $x_H = 1$. The other parameter values are $\delta = 0.1$ and $c = 0.03$. The last column gives a boom case example, where x_H and δ are increased by 10% to 1.10 and 0.11, while c is reduced by 10% to 0.027. The other columns present results for the base case parameters with only one other variable changed to its boom level. The results for x_H and c are straightforward. The asking price schedule shifts up and the maximum search increases. The 10% increase in δ from a small level shifts the demand schedule up for low n. When n becomes higher, the demand schedule shifts down. This is because of the increased likelihood of the bidding war case. The table also illustrates the boundedness of demand; the possibility of a bidding war caps the number of visitors who can be attracted.

Table B-2 presents a parallel analysis for house atypicality. The first column repeats the base case analysis above. As noted in the text, one way to conceive of atypical houses is that they are less likely to be well-matched to visitors. The second column of Table B-2 presents this case, with $\delta = 0.9$. The simulations show that the demand schedule shifts down. The third column presents results for an alternate conception of atypicality, one where a smaller probability of a good match, $\delta = 0.9$, and a larger value of the good match such that δx_H remains constant. In the simulations reported in Table B-2, the demand schedule shifts up.

Finally, Table B-3 present results that relate to the sensitivity of demand to changes in asking price on search in busts and for atypical houses. The table reports the reduction in asking price required to encourage one additional visit for various levels of visits. The first column reports the base case values. The second reports the values for a bust or atypical house, where $\delta = 0.09$, and nothing else changes. The third reports the alternative atypicality approach, where $\delta = 0.09$ and δx_H remains constant. Comparing the first and second columns shows that visits to atypical houses are more sensitive to asking price for high asking prices, but the relationship is reversed for high asking prices. The relationship is ambiguous, as noted in the text. Comparing the second and third columns, one sees that sensitivity is the same between the two conceptions of inequality for any level of visits other than n = 1 and n =13. This is a consequence of the functional form of a_n in (IV.9) in the text.

Table B-1. Booms and Demand

n	base	delta+10%	delta+20%	xH+10%	c-10%	all + 10%
1	0.700	0.727	0.750	0.800	0.730	0.855
2	0.667	0.694	0.716	0.767	0.700	0.824
3	0.630	0.656	0.677	0.730	0.667	0.790
4	0.588	0.613	0.633	0.688	0.630	0.752
5	0.543	0.565	0.583	0.643	0.588	0.709
6	0.492	0.512	0.526	0.592	0.543	0.660
7	0.435	0.451	0.462	0.535	0.492	0.606
8	0.373	0.383	0.388	0.473	0.435	0.545
9	0.303	0.307	0.305	0.403	0.373	0.476
10	0.226	0.222	0.210	0.326	0.303	0.399
11	0.140	0.125	0.102	0.240	0.226	0.313
12	0.044	0.017	-	0.144	0.140	0.216
13	-	-	-	0.038	0.044	0.106

Note: This table presents the demand schedule (i.e., asking price for a given number of visitors) for various parameter values. In the base case, we normalize $x_L = 0$; $x_H = 1$; $\delta = 0.1$ and $c = 0.03$. In the boom case, we set $x_L = 0$; $x_H = 1.1$; $\delta = 0.11$ and $c = 0.027$. In other cases, we present the results for the base case parameters with only one parameter changed to its boom level. Cells with “-“ indicate that there is no asking price that would encourage the corresponding level of visits.

Table B-2 Atypicality and Demand

n	base	delta-10%	delta-10%; x_H+10%
1	0.700	0.667	0.778
2	0.667	0.634	0.745
3	0.630	0.597	0.709
4	0.588	0.558	0.669
5	0.543	0.514	0.625
6	0.492	0.466	0.577
7	0.435	0.413	0.524
8	0.373	0.355	0.466
9	0.303	0.291	0.402
10	0.226	0.221	0.332
11	0.140	0.144	0.255
12	0.044	0.059	0.170
13	-	-	0.077

Note: This table presents the demand schedule (i.e., asking price for a given number of visitors) for various parameter values. In the base case, we normalize $x_L = 0$; $x_H = 1$; $\delta = 0.1$ and $c = 0.03$. For Atypicality, we reduce the probability of a good match to $\delta = 0.09$ in the second column and reduce $\delta = 0.09$ while keeping δx_H constant in the third column. Cells with “-“ indicate that there is no asking price that would encourage the corresponding level of visits.

Table B-3. Busts, Atypicality, and the Sensitivity of Demand

n	base	delta-10%	delta-10%; x_H+10%
1	0.500	0.333	0.222
2	0.056	0.033	0.033
3	0.062	0.036	0.036
4	0.069	0.040	0.040
5	0.076	0.044	0.044
6	0.085	0.048	0.048
7	0.094	0.053	0.053
8	0.105	0.058	0.058
9	0.116	0.064	0.064
10	0.129	0.070	0.070
11	0.143	0.077	0.077
12	0.159	0.085	0.085
13	-	-	0.093

Note: This table presents the sensitivity demand schedule (i.e., the amount that asking price must be reduced to obtain the nth visitor) for various parameter values. In the base case, we normalize $x_L= 0$; $x_H = 1$; $\delta = 0.1$ and $c = 0.03$. The second column reports results for a reduction in the probability of a good match to $\delta = 0.09$. The third column reports results for the alternate atypicality calculation where we reduce $\delta = 0.09$ while keeping δx_H constant. For the first row, the reduction is relative to an asking price equal to 1. For the others, the reduction equals a(n+1) – a(n).

Online Appendix C. Additional Estimates

This Appendix presents additional estimates that serve to establish the robustness of the paper's key results. Table C-1 presents results employing an alternate characterization of the boom/bust state of the housing market. Specifically, instead of employing a bust dummy as in the preferred models – an approach that fits the sample market well – the percent changes in median market price and sales are employed as controls. The interacted coefficients are positive and significant, meaning that a decrease in asking price has a smaller effect in a boom. The table thus shows clearly that the paper's result on the stronger directing role of asking price in a bust continues to hold.

Table C-1: Bidder Response to Asking Price: Market Changes and Atypicality

Dependent Variable	Ln(Number of Bidders) (1)	(4)	(5)	(6)
Ln(Ask Price)	-0.14	-0.25	-0.12	-0.22
	(-4.03)	(-2.87)	(-2.95)	(-3.49)
Ln(Ask Price)*Atypicality	-0.01	-0.02	-0.01	-0.02
	(-1.97)	(-3.02)	(-2.08)	(-4.65)
Ln(Ask Price)* Changes in Market Price (%)	0.93	0.92		
	(1.72)	(4.23)		
Ln(Ask Price)*Changes in Sales (%)			0.25	0.24
			(2.40)	(1.75)
Period	Yes	No	Yes	Yes
District	Yes	Yes	Yes	Yes
House Attributes	No	Yes	No	Yes
Property Tax Assessment	No	No	No	No
Obs.	2891	2891	2891	2891
Ln(Ask Price)	-0.36	-0.40	-0.33	-0.38
	(-4.18)	(-13.47)	(-4.26)	(-2.72)
Ln(Ask Price)*Atypicality	-0.01	-0.02	-0.01	-0.02
	(-1.69)	(-4.67)	(-2.35)	(-2.05)
Ln(Ask Price)* Changes in Market Price (%)	0.80	0.80		
	(1.60)	(3.26)		
Ln(Ask Price)* Changes in Sales (%)			0.21	0.21
			(1.64)	(4.08)
Period	Yes	Yes	Yes	Yes
district	Yes	Yes	Yes	Yes
House Attributes	No	Yes	No	Yes
Property Tax Assessment	Yes	Yes	Yes	Yes
Obs.	2667	2667	2667	2667

Note: This table reports estimates from the log-linear regressions of the number of bidders on the asking price, with a variety of controls. Standard errors are bootstrapped. T-statistics are reported in brackets. The number of bidders is reported by buyers, and other variables are reported by the MLS. The atypicality index is constructed to measure the degree of unusual features of a property based on Haurin (1988). The top panel excludes tax values and tax year dummies, while the bottom panel includes them.