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

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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 the asking price, which might suggest that asking price has limited relevance. However, many housing transactions involve a sales price equal to asking price (a previously unnoticed fact), strongly suggesting that asking price does matter. The paper develops a model where asking price is neither a binding commitment nor even a ceiling yet still directs buyer search and thus impacts sales price.   Using novel survey data, the paper provides empirical evidence consistent with asking price playing a directing role in buyer search.

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 find themselves unwilling to pay the asking price, leading them to negotiate the price down. Although there are exceptions, this typically does not occur in retail markets with posted prices. Second, buyers may find themselves competing among each other with sufficient vigor that the ultimate purchaser pays a price that is greater than the posted list price. Again, although there are exceptions, this also does not typically occur in standard retail markets with posted prices.

It is tempting to conclude from this that the asking price for real estate is of limited relevance. A seller can set a low asking price and let the buyers compete the sales price up. Or instead, a seller can set a high asking price and negotiate down. Whether or not asking price is indeed irrelevant 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. The theory is motivated by three key stylized facts. First, as noted above, a house's ultimate sales price is frequently below asking price. Ortalo-Magne and Merlo (2004) find that the average ratio of sales price to list 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 (2012) show that the ratio is also 96% for the same period. Not surprisingly, this means that a very significant fraction of sales are below list (Case and Shiller, 1988 and 2003).[1] These descriptive statistics show that asking price is certainly not a posted price. And it really never has been.

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 (2012) find a similar percentage at the same time in US NAR data. Recent years, however, have frequently had 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 it fell, but at

[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.

close to 10% the share 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 list 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 or a floor.

Does this mean that the asking price is irrelevant? 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 idiosyncratic valuation. In a Dutch auction, price will depend on the expectation of the second highest idiosyncratic valuation. In either case, with a continuous and atomless distribution generating the valuations, there is zero probability of asking price equaling sales price.

The third key stylized fact – one that has not previously be emphasized– contradicts this irrelevance result: it is now and always has been 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% In an ongoing survey of homebuyers in a large North American metropolitan area (described in Section VI below), we find 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 the asking price matters. But the question remains: why does it matter?

This paper presents a model of optimizing agents where asking price plays an important role in house sales. The explanation relies on the asking price acting as a ceiling only in some situations. The above discussion makes clear that a house not being 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. Specifically, the listing contract typically includes a clause requiring the seller to pay the agent's commission if the seller rejects an unrestricted offer equal

[2] Case and Shiller (2003) also report a growth in the fraction of sales above list in the four cities that they survey.

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.

Previous models of this commitment typically treat the asking price as a binding ceiling. In Chen and Rosenthal (1996a), the seller sets such a ceiling.[3] Buyers make decisions of whether or not to incur the search costs associated with visiting the house and thus learning whether or not the house is a good match for them. 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, giving the prospective buyers incentives to search. By setting a lower asking price, the seller encourages more buyers to visit, which increases 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 the asking price is to encourage visits.

This paper develops a model of commitment and search that is consistent with the three key empirical facts discussed above. The model establishes that the commitment role of asking price remains, even when it is no longer always a binding ceiling. It does so by laying out a model of asking price as a commitment that will allow for bidding wars. Specifically, we suppose that asking price is binding only in the case where there is only one buyer who is willing to bid above it. In this case, and not when there are multiple buyers willing to pay more than asking price, a seller would be violating standard norms of good faith bargaining if he rejects the offer. This would expose the buyer to financial risk given the provisions of standard agency contracts. In this setup, the analysis shows that the commitment feature can persist even when bidding wars are allowed, but in a modified way, with the seller facing a different tradeoff. As in Chen and Rosenthal, starting with a very high asking price, a reduction in asking price can encourage search by increasing the buyer's surplus in some states of nature.

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

[3] See also the related paper, Chen and Rosenthal (1996b).

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. Since an increase in the number of bidders increases the likelihood of a bidding war, this also reduces the likelihood of commitment. This effect 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 from another buyer.

This analysis then can be used to solve for the optimal asking price for a particular house. There are several forces at work. In the case where the commitment binds, the seller's expected profit is greater with a higher asking price all else equal. However, there is also an indirect effect of asking price on the probability of the commitment state through the dependence of the number of visitors on asking price. Similarly, a lower asking price also increases the probability of the bidding war and decreases the probability of traditional sales. The asking price, thus, directs search by impacting the number of visits and hence the expected sales price. The optimal asking price then maximizes the seller's objective function, taking the visit relationship as given.

There are several features of this model's equilibrium that are worthy of comment. First, the asking price matters in this model because it is a conditional commitment to restrain the price, which serves to encourage visits. Asking price is, thus, actively directing search. Second, a very high asking price discourages visits because of the high likelihood that the commitment will be irrelevant. Third, a low enough asking price need not encourage visits, since it would also increase the likelihood that the commitment would not be relevant. In this case, buyers anticipate obtaining a low surplus because they know they will face fierce competition from other bidders. Fourth, we suppose that both the buyer and the seller incur costs associated with a buyer's visit to the seller's house. This assumption, which we believe is realistic, means that although the seller would benefit from having many visitors because the likelihood of a good match would rise, the seller does bear costs associated with visits, and so the seller does not always unambiguously benefit from more visits.

In addition to modeling the role of asking price, the paper also carries out an empirical analysis of the asking price by considering several 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 (see below) 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 from a large North American metropolitan area that is unique in including data on 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. Consistent with the model, we find that a lower asking price reduces 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, which is also consistent with the model's predictions. 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 below- and above-list results are predicted by the model, while the model's predictions are ambiguous regarding the share of sales at list price.

The paper contributes to the growing literature on housing market microstructure. Theoretical research on housing market microstructure begins with Yinger's (1981) random matching model. Other random matching approaches include Haurin (1988), Piazzesi and Schneider (2009) and Novy-Marx (2009). Since random matching models do not model the role of the asking price, they are of less relevance to our paper. In contrast, the directed search models of housing markets have explicitly modeled how asking price impacts buyers' search activity and hence transaction outcome. Notable examples include Chen and Rosenthal (1996) Arnold (1999), Green and Vandell (1998).[4] Their papers differ from ours in that they treat the asking price as a ceiling, while we allow for the possibility of bidding wars where the sales price exceeds the asking price. In this regard, Albrecht et al (2012) is closer to our analysis in that their directed search model also allows for asking price to be above, below, or equal to asking price. A key difference between our work and Albrecht et al is that their model assumes that visitors do not know the number of other visitors, implying that high and low asking prices give equivalent revenues to sellers. Our model, in contrast, allows the number of visitors to respond to the asking price. As a result, the asking price plays a central role in sellers' payoff.

On the empirical side, Merlo and Ortalo-Magne (2004) establish, among other things, a negative relationship between list price and sale hazard. Sass (1988) is an earlier paper on list

[4] For directed search models of markets other than housing, see Peters (1984, 1991), Shi (1995), and Moen (1997). Since they do not focus on housing, these models do not allow for the housing-market phenomenon of sales prices that can exceed, equal, or fall below the asking price.

price reductions. Anglin et al (2002), Knight (2002), and Haurin et al (2010) consider the empirical relationship between asking price, selling price, and time on market. Carrillo (2012) estimates an equilibrium search model and recovers the amount of information that the asking price reveals to buyers and the effects of asking price on time on the market. However, given the lack of data on home search activity, none of these papers estimate the directing role of the asking price in the home search process. One exception is Genesove and Han (2012b) who consider the role of the asking price when estimating how the sales price changes with the number bidders.   Unlike the current paper, however, Genesove and Han focus on the dispersion in buyers' valuation for the same house rather than the directing role of the asking price.

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 individual city data shows a similar pattern, bearing in mind that there is variation between the cities. For instance, the share of at-list sales in San Francisco hardly grew at all (26.8% to 27.5%), while the share of above-list sales grew less in in Los Angeles (6.3% to 19.9%).

The significant shares of above-list and at-list sales documented by Case and Shiller (1988, 2003) are roughly consistent with the evidence reported by a more systematic home buyer and seller survey conducted by Research Division of the National Association of Realtors (NAR). A detailed description of the NAR survey is provided in Genesove and Han (2012a) and Han and Strange (2012).

Table 2 presents the NAR-reported shares of below- and at-list sales over the period 2003-2010.[5] 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.[6] 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 period when the housing market slowed down, 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. These boom and bust variations in the below-list and acceptance sales are consistent with what were reported by 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 in a commitment from the seller in certain circumstances and thus rewarding and encouraging buyer search. The model will have predictions about 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, a more refined survey dataset that contains detailed

[5]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.

[6]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.

information on both house characteristics and search activity. This will permit an empirical test of the predictions generated from our model.

At this point, we will now lay out the model.

III. Model

This section specifies a 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. Extensions are discussed later in the paper.

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. Albrecht et al (2012) also take a one period approach. We have chosen this specification because it is the most direct way to allow for both the possibility of traditional negotiations between one buyer and a seller and also the current practice of having multiple simultaneous offers on a house. A standard arrival model would preclude the latter possibility.

There is one house. 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. 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 the visit and of absenting oneself during it.[7] These must be 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. This setup is a discrete version of a standard matching model in the Diamond (1982) and Mortensen-Pissarides (1994) tradition.

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

[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.

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, 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.

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 have some commitment attached to it. As noted elsewhere in the literature, there is usually not a legal requirement that a seller transmit a house to a buyer who makes an offer at or equal to the asking price. However, sales agreements with listing agents typically include provisions requiring 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 other agents buyers. 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

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

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

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 buyers have visited the house.

A. Pricing: when does a price ceiling bind?

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 the random 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.

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[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.

The results of a continuous specification are similar, if less clear. They are discussed below, with details presented in the Appendix.

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

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 therefore 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.

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

[10] It is worth observing that in this setup there is no probability of a house failing to sell. It would be easy to change the model in a way that would generate failures to sell 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.

believe that this is realistic; real estate agents assisting buyers and sellers routinely inform their clients of the market level of interest in particular properties.[11]

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 the incentive for search and the lower must be the asking price in order to give an additional search incentive. Suppose that the 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.[12] 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): $\theta \geq 1 - c/[\delta[x_H - x_L]]$

[11]By making this assumption, our approach differs sharply from Albrecht et al (2012). In that model, the only way that asking price directed search was by signaling seller reservation price rather than by encouraging search. Our focus here is, in contrast, on the latter issue.
[12] They later show that their analysis follows with some modification under weaker bargaining assumptions.

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.

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 consider 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 buyergets 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:

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

This result extends the Chen-Rosenthal (1996) 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

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

This is in contrast to the Chen-Rosenthal model of a price ceiling. In that model, 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.

Some additional properties are also worthy of mention. A third property of the demand schedule is that its elements 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. Fourth, 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. Fifth, 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).

A boom might also be related to δ, the probability that any particular buyer obtains a good match. The impact of δ on the demand schedule, is, however, more complicated than the impact of c or x_H. 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. A As n becomes large, the relationship eventually becomes negative. This is because the probability of a buyer's competing with other well-matched buyers rises as δ becomes larger. We will return to this issue below when we consider the relationship between the state of the housing market – boom or bust – and the asking price.

Table 3a illustrates these effects. The table presents the demand schedule for various parameter values. 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 $c = 0.05$. The last column gives a boom case example, where x_H and δ are increased by 20% to 1.20 and 0.12, while c is reduced by 20% to 0.04. 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 20% increase in δ from a small level also shifts the demand schedule up. Table 3b considers only the effects of increases in δ. It confirms the point made above that the effects of δ on a_n are ambiguous. For a large enough δ, the demand schedule shifts down for large n. This is because of the increased likelihood of the bidding war case.

At this point, the remaining task is to consider the seller's choice of asking price.

V. Strategic asking price

A. The house seller's choice

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

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

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

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

It is straightforward to see that the seller will choose from the demand schedule ***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 ***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:

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

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

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

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 setting extreme asking prices, at either x_L or x_H, was dominated for the seller. It is now possible to show this. First, an asking price equal to x_H encourages no 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 a 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 3: 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.

B. Asking prices in booms and busts.

In addition to establishing the commitment role of asking price in this general setting, we are also seeking to explain the behavior of asking price in boom vs. bust markets. The frequency of above list sales is often employed as an indicator of market strength, and our model allows us to explore this formally.

The first step in doing this is to consider how the elements of our stylized model relate to a market's boom or bust condition. The model focuses on the sale of one house, and is thus an open model. Any variables that we associate with a boom should be associated with increases in the number of visitors and increases in sales price, since both of these are clearly pro-cyclical. There are two variables that clearly have this property: c and x_H.

A decrease in buyer search costs or an increase in good match quality leads to more visitors for every level of asking price by (IV.6). A decrease in buyer search costs or an increase in match quality decreases ϕ and thus $\Delta\pi_n$ for all n. A large enough change will thus have the effect of further increasing n.

How, then, do changes in these variables impact the nature of housing transactions in equilibrium? The previously noted positive effect implies that the fraction of below-list, traditional, sales will fall since we have $\tau = (1-\delta)^n$. This means that $\alpha + \beta$ will rise automatically since there will be more sales at or above list. Since a bidding war requires two or more buyers who are good matches to the house, the probability of a bidding war rises with the number of bidders, and the fraction of sales with price strictly above list must rise. The probability of acceptance, $\alpha = n\delta(1-\delta)^{n-1}$, is ambiguously related to buyer search costs. In a boom associated with either a reduction in buyer search costs or in a better quality good match there will be fewer traditional below-list sales and more bidding wars, with the share of sales associated with sales price equal to asking price ambiguous.

The effect of an increase in the probability of a good match is ambiguous. As above, an increase in δ has an ambiguous effect on n. Regarding ϕ and $\Delta\pi_{n,}$ an increase in δ has a positive effect on ϕ for low δ and a negative effect for high δ. When δ is low, an increase raises the *ex ante* expected value of search, which tends to result in more visitors and increases in the share of above list sales and of prices. When δ is instead high, an increase still raises the probability of a searcher realizing a good match with the house. It also, however, raises the probability of ending up in a bidding war with no surplus. The latter effect dominates for high δ. This matching aspect of a boom, therefore, has ambiguous effects on the nature of the equilibrium housing transaction.

All of this can be illustrated by some examples. Table 4a presents illustrations of the seller's profit schedule. The base case parameters are as above in Table 3. Moving from the base case ($x_L = 0$, $x_H = 1$, c = 0.05, s = 0.03, $\delta = 0.1$) to the boom case ($x_L = 0$, $x_H = 1.4$, c = 0.04, s = 0.03, $\delta = 0.12$) leads to a seller strategy involving a higher asking price but more search. In the boom we have a smaller share of traditional sales but a greater share of sales equal to list price and of bidding wars. Table 4b shows results where only δ is higher in the boom. For $\delta = 0.2$, we have a situation resembling the general boom: higher asking price, more search, fewer traditional sales, more acceptance sales, and more bidding wars. For $\delta = 0.4$, we have a quite different pattern: asking price is considerably lower. This does not result in more search than in the $\delta= 0.2$ case, but it does result in many more bidding wars. This is an instance of using a deliberately low asking price to maintain search in the anticipation of the bidding war that is likely to ensue when the probability of a good match is large.

The results, thus, have a fairly consistent pattern. The seller employs the asking price to encourage search. For low δ, a low asking price encourages search, which offers enough rewards to the seller to compensate in expected value for the cost of the low asking price commitment. The seller is limited in how low an asking price can be set by the fact that buyers will anticipate the possibility of a bidding war which – in this setting where asking price is not exactly a ceiling – would remove the commitment from which they benefit. In addition, the seller also incurs marginal costs related to buyer visits, further leading the seller away from setting a very low asking price.

C. Comments

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 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.[13] 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 of this model 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.

[13] Details are presented in the Appendix.

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 because they do not include variables that measure the amount of search received by a particular house. In addition, they include 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. To conduct surveys in metropolitan area, we 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 purpose. 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%. A detailed description of this ongoing survey is provided in Genesove and Han (2012b).

The questionnaires sought information on home search, bargaining and bidding behavior. Two questions that are mostly relevant to this paper 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 in purchasing a home, and hence permit an empirical investigation of role of the asking price in directing buyers' search activity. To the best of our knowledge, this information has never been collected previously.

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 from the sample.

Table 5 presents descriptive statistics from the survey data. Two patterns emerge. First, there is a notable fraction for each of the below-, at-, and above-list sales. This is consistent with what we observed from the Case/Shiller Survey and the NAR survey. Although the magnitude of the acceptance rates documented in our survey is substantially below that in the U.S. surveys, the cyclical variation in the acceptance rates and in the traditional (below list) sales is still highly in line with what we observed from the U.S. markets.[14] 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 survey we conducted 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 5, 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.

B. Empirical results: The directing role of asking price

The key implication of the model is that a lower asking price is required to encourage 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.

[14] 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 list price. Nevertheless, the fraction of acceptance is large enough that it calls for a model to explain the forces at work.

Specifically, we present a log-linear specification that regresses the number of bidders on the asking price. To the best of our knowledge, ours is the only paper in the housing microstructure literature that provides empirical evidence on directed search.

The top panel of Table 6 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 attributes which increases the coefficient further to 0.136.[15] 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 of properties, 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 central directing role of the asking price in home buyers' search process.

A further investigation of equation (IV.7) shows that

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

and

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

(VI.1) indicates that the more high-value buyers are, the weaker is the negative effect of the asking price on the number of bidders. The second expression indicates that the larger fraction is the high type buyers, the weaker is the negative effect on the number of bidders. Together, these

[15] 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.

two expressions imply that 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 value a given house more, it requires less reduction in the asking prices to induce a given number of visits.

To test this implication, we use the 2008 financial crisis as an empirical proxy for the bust period. For the market under our investigation, the sample period under our investigation started with a boom market in 2006, followed by a slow and uncertain market trigged by the global financial crisis started in September 2008. However, the market did not experience out of the ordinary rates of foreclosures as in the most U.S. markets. By the early 2009, the housing market in this area started rising again. For this reason, we consider the September, 2008–December, 2008 as a period when the financial crisis hit the market, which in turn proxies for the housing market bust during the sample period.

In Table 7, we expand the regressions in Table 6 by including the interaction of the asking price and the crisis period dummy. Beginning with the top panel, the coefficient on asking price alone is positive when the district dummies are not included (Columns 1-3) but significantly negative once the district dummies are included (Columns 4-6). This is the same pattern that appeared in Table 6. More importantly, in all specifications, the coefficient on the interaction variable is negative and statistically significant. In particular, in Column 6 where transaction dummies, district dummies and housing attributes are all controlled for, the coefficient on the asking price is -0.19 (significant at the 1% level) and the coefficient on the interaction variable 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% in normal times and by 3.5% in busts. These findings are highly consistent with cyclical variation in the directing role of the asking price predicted by the model.

The estimated effect of the asking price on the search intensity, although qualitatively consistent with what the model predicted, seems small in magnitude. This should be treated as a lower bound for the true directing effect of the asking price for several reasons. First, we have used 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. In the context of such a model, our estimates of the relationship between asking price and bidding would underestimate the strength of the asking price – visits relationship. Second, it is possible that the number of bidders is mis-reported by homeowners we surveyed. 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 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 tax value, along with tax year dummies, as an attempt 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 6 presents the results of models that include controls for taxes and tax years. Given the importance of home locations, we focus our discussion on the last 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 – lowing 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 highly consistent with what we expected from an errors-in-variable bias 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 the 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 predicted by the theory.

Turning to the bottom panel of Table 7, where the asking price is interacted with the financial crisis dummy, we find that our main results are again robust to the inclusion of taxes. In particular, in the bottom panel where taxes are controlled for, the effect of the asking price alone on the number of bidders becomes stronger both economically and statistically. Moreover, consistent with what we expected, such effect is strengthened in the housing market bust, with a 10% reduction in the asking price increasing the number of bidders by about 5%.

C. 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 ambiguous in its predictions regarding the fraction of sales that involve the acceptance of the asking price, as illustrated in the examples presented in Table 4. It is real estate agent folk wisdom that more sales above list is observed in a boom market. 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 the acceptance case, we are not testing the model here but attempting to determine which of the theoretical possibilities is consistent with observation.

With that in mind, Table 8 presents results from regressing a set of dummy variables that indicate the incidence of traditional/bidding /acceptance-sales on a bust proxy and a variety of control variables. As before, we proxy the bust period by the financial crisis indicator. In all specifications, we control for property characteristics, neighborhood conditions, and transaction period dummies.

For the traditional (below-list) sales, the coefficient on the financial crisis indicator is 1.58 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 22.8% greater during the bust than in more normal circumstances.

Turning to the bidding war (above-list) sales, the coefficient on the financial crisis indicator is -0.79 and significant at the 10% level, indicating that the predicted probability that a house ends up with an above-list price is 9% during a bust. Together, these two 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.

Finally, although our model does not deliver unambiguous predictions about the cyclical variations in the acceptance rates, the last column of Table 8 shows that the occurrence of acceptance sales is much less likely in a bust than in a boom. This is also consistent with the descriptive evidence presented in the Case/Shiller survey, NAR survey, and the survey we conducted.

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 is shown to encourage 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, at least in the sort of microeconomic model that the paper proposes.

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 boom than in a bust. 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. This is 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.

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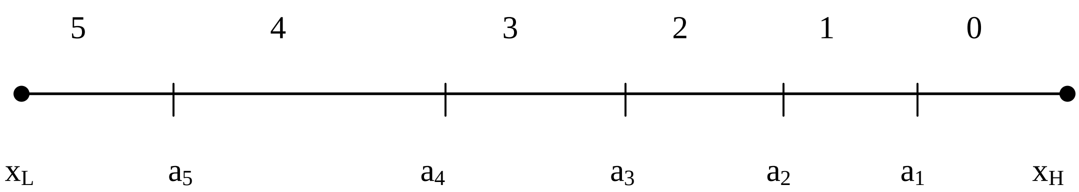
Figure 1. Asking price and search



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.

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

	Los Angeles		San Francisco		Boston		Milwaukee		Average	
	1988	2003	1988	2003	1988	2003	1988	2003	1988	2003
P>A	6.3	19.9	9.8	45.8	10.5	21.3	3.3	17.5	4.9	25.5
P=A	38.0	50.4	26.8	27.5	23.5	59.1	22.7	52.4	27.9	48.4
P<A	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). P>A indicates "above-list sales," P=A indicates "at-list sales," P<A indicates "below-list sales."

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

	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%	57.08%	29.43%	97.79%	54.88%	31.29%	97.71%	62.47%	24.86%
	(33,188)	(33,188)	(33,188)	(23,585)	(23,585)	(23,585)	(9,603)	(9,603)	(9,603)
2007-2010	94.82%	74.29%	17.48%	94.93%	72.81%	18.29%	94.42%	79.61%	14.55%
	(40,288)	(40,288)	(40,288)	(31,547)	(31,547)	(31,547)	(8,741)	(8,741)	(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 3a - Demand Schedule - Boom and Bust

n	base	$x_H = 1.2$	c = 0.4	$\delta = 0.12$	boom
1	0.500	0.700	0.600	0.583	0.867
2	0.444	0.644	0.556	0.527	0.821
3	0.383	0.583	0.506	0.462	0.770
4	0.314	0.514	0.451	0.389	0.711
5	0.238	0.438	0.390	0.305	0.644
6	0.153	0.353	0.323	0.210	0.568
7	0.059	0.259	0.247	0.103	0.482
8	0.000	0.155	0.164	0.000	0.384
9	0.000	0.038	0.071	0.000	0.273
10	0.000	0.000	0.000	0.000	0.147
11	0.000	0.000	0.000	0.000	0.003
12	0.000	0.000	0.000	0.000	0.000

Table 3b - Demand Schedule - Match Quality

n	base	δ= 0.2	δ= 0.3	δ= 0.4	boom
1	0.500	0.750	0.833	0.875	0.900
2	0.444	0.688	0.762	0.792	0.800
3	0.383	0.609	0.660	0.653	0.600
4	0.314	0.512	0.514	0.421	0.200
5	0.238	0.390	0.306	0.035	0.000
6	0.153	0.237	0.008	0.000	0.000
7	0.059	0.046	0.000	0.000	0.000
8	0.000	0.000	0.000	0.000	0.000
9	0.000	0.000	0.000	0.000	0.000
10	0.000	0.000	0.000	0.000	0.000
11	0.000	0.000	0.000	0.000	0.000
12	0.000	0.000	0.000	0.000	0.000

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; δ = 0.1 and c = 0.05. In the boom case, we set x_L= 0; x_H = 1.2; δ = 0.12 and c = 0.04. In other cases, we present the results for the base case parameters with only one parameter changed to its boom level.

Table 4a - Asking Price, Profit, and Transaction-Types: Boom and Bust

	base					boom				
n	a(n)	τ	α	β	profit	a(n)	τ	α	β	profit
1	0.500	0.900	0.100	0.000	0.020	0.867	0.880	0.120	0.000	0.074
2	0.444	0.810	0.180	0.010	0.030	0.821	0.774	0.211	0.014	0.131
3	0.383	0.729	0.243	0.028	0.031	0.770	0.681	0.279	0.040	0.172
4	0.314	0.656	0.292	0.052	0.024	0.711	0.600	0.327	0.073	0.200
5	0.238	0.590	0.328	0.081	0.010	0.644	0.528	0.360	0.112	0.217
6	0.153	0.531	0.354	0.114	0.000	0.568	0.464	0.380	0.156	0.223
7	0.059	0.478	0.372	0.150	0.000	0.482	0.409	0.390	0.201	0.220
8	0.000	0.430	0.383	0.187	0.000	0.384	0.360	0.392	0.248	0.208
9	0.000	0.387	0.387	0.225	0.000	0.273	0.316	0.388	0.295	0.190
10	0.000	0.349	0.387	0.264	0.000	0.147	0.279	0.380	0.342	0.166
11	0.000	0.314	0.384	0.303	0.000	0.003	0.245	0.368	0.387	0.136
12	0.000	0.282	0.377	0.341	0.000	0.000	0.216	0.353	0.431	0.101
13	0.000	0.254	0.367	0.379	0.000	0.000	0.190	0.336	0.474	0.062
14	0.000	0.229	0.356	0.415	0.000	0.000	0.167	0.319	0.514	0.020
15	0.000	0.206	0.343	0.451	0.000	0.000	0.147	0.301	0.552	0.000

Note: This table presents the seller's profit schedule for various parameter values. In the base case, we normalize $x_L = 0$; $x_H = 1$; $\delta = 0.1$, c = 0.05, and s = 0.03. In the boom case, we set $x_L = 0$; $x_H = 1.4$; $\delta = 0.12$, c = 0.04, and s = 0.03.

Table 4b - Asking Price, Profit, and Transaction-Types: Match Quality

	boom (delta = 0.2)					boom (delta = 0.4)				
n	a(n)	τ	α	β	profit	a(n)	τ	α	β	profit
1	0.850	0.800	0.200	0.000	0.140	0.925	0.880	0.400	0.000	0.340
2	0.813	0.640	0.320	0.040	0.240	0.875	0.774	0.480	0.160	0.520
3	0.766	0.512	0.384	0.104	0.308	0.792	0.681	0.432	0.352	0.604
4	0.707	0.410	0.410	0.181	0.350	0.653	0.600	0.346	0.525	0.630
5	0.634	0.328	0.410	0.263	0.372	0.421	0.528	0.259	0.663	0.622
6	0.542	0.262	0.393	0.345	0.378	0.035	0.464	0.187	0.767	0.593
7	0.428	0.210	0.367	0.423	0.370	0.000	0.409	0.131	0.841	0.552
8	0.285	0.168	0.336	0.497	0.352	0.000	0.360	0.090	0.894	0.503
9	0.106	0.134	0.302	0.564	0.326	0.000	0.316	0.060	0.929	0.450
10	0.000	0.107	0.268	0.624	0.293	0.000	0.279	0.040	0.954	0.394
11	0.000	0.086	0.236	0.678	0.254	0.000	0.245	0.027	0.970	0.336
12	0.000	0.069	0.206	0.725	0.211	0.000	0.216	0.017	0.980	0.278
13	0.000	0.055	0.179	0.766	0.165	0.000	0.190	0.011	0.987	0.219
14	0.000	0.044	0.154	0.802	0.116	0.000	0.167	0.007	0.992	0.159
15	0.000	0.035	0.132	0.833	0.065	0.000	0.147	0.005	0.995	0.100

Note: This table presents the seller's profit schedule for various values of δ in the boom case.

Table 5: Descriptive Statistics 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 an on-going survey conducted among recent home buyers in a large North American metropolitan area.

Table 6: Bidder Response to Asking Price

Dependent Variables	lnBIDDER (1)	(2)	(3)	(4)	(5)	(6)
lnASK	0.08	0.09	0.136	-0.14	-0.12	-0.22
	(2.98)	(1.61)	(3.90)	(-3.85)	(-3.43)	(-3.78)
Period	No	Yes	Yes	No	Yes	Yes
district	No	No	No	Yes	Yes	Yes
Attributes	No	No	Yes	No	No	Yes
Taxes	No	No	No	No	No	No
Obs.	2947	2947	2891	2947	2947	2891
lnASK	0.20	0.20	0.12	-0.36	-0.33	-0.40
	(4.91)	(4.88)	(2.48)	(-5.08)	(-4.60)	(4.87)
Period	No	Yes	Yes	Yes	Yes	Yes
district	No	No	No	No	Yes	Yes
Attributes	No	No	Yes	No	No	Yes
Taxes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2708	2708	2667	2708	2708	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 reported in brackets. The number of bidders is reported by buyers, and other variables are reported by the MLS. The top panel exclude tax values and tax year dummies, while the bottom panel include them.

Table 7: Cyclical Variations in Bidder Response to Asking Price

Dependent Variable	lnBIDDER (1)	(2)	(3)	(4)	(5)	(6)
lnASK	0.085	0.010	0.160	-0.126	-0.097	-0.19
	(3.19)	(3.44)	(4.32)	(-3.58)	(-2.61)	(-3.21)
lnASK*crisis	-0.009	-0.099	-0.14	-0.009	-0.146	-0.16
	(-4.16)	(-1.38)	(-1.92)	(-4.05)	(-2.06)	(-2.19)
Period	No	Yes	Yes	No	Yes	Yes
district	No	No	No	Yes	Yes	Yes
Attributes	No	No	Yes	No	No	Yes
Taxes	No	No	No	No	No	No
Obs.	2947	2947	2891	2947	2947	2891
lnASK	0.20	0.22	0.145	-0.359	-0.308	-0.372
	(4.97)	(5.02)	(2.89)	(-5.03)	(-4.18)	(-4.44)
lnASK*crisis	-0.008	-0.092	-0.124	-0.008	-0.103	-0.127
	(-2.97)	(-1.23)	(-1.62)	(-2.97)	(-1.41)	(-1.78)
Period	No	Yes	Yes	No	Yes	Yes
district	No	No	No	Yes	Yes	Yes
Attributes	No	No	Yes	No	No	Yes
Taxes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2708	2708	2667	2708	2708	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 reported in brackets. The number of bidders is reported by buyers, and other variables are reported by the MLS. The top panel exclude tax values and tax year dummies, while the bottom panel include them.

Table 8: Cyclical Variations in the Nature of Sales

Dependent Variable	Traditional Sales Indicator	Bidding War Sales Indicator	Acceptance Sales Indicator
Crisis	1.58 (3.77) (0.22)	-0.79 (-1.74) (-0.09)	-1.13 (-2.55) (-0.08)
Period	Yes	Yes	Yes
District	Yes	Yes	Yes
Attributes	Yes	Yes	Yes
Obs.	2637	2637	2637

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 reported in brackets. The indicator of below-, at-, and above-list sales is based on buyers' reports, and other variables are reported by the MLS.

Appendix – 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

$$\begin{aligned} \nu_1 &= \int_{xL}^{xa}\left(x - p(x)\right)f(x)dx + \int_{xa}^{xH}\left(x - a\right)f(x)dx - c \\ &= E(x) - c - \alpha a - (1-\alpha)[\theta E(x|x<x_a)+(1-\theta)x_L] \end{aligned} \tag{A.2}$$

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

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

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 $a = a_1$,

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

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 $(x_{(1)},x_{(2)}) \in T = \{(x_{(1)},x_{(2)})|\ \theta\, x_{(1)} + (1-\theta)x_{(2)} \le a\}$. An acceptance occurs when $(x_{(1)},x_{(2)}) \in A = \{(x_{(1)},x_{(2)})|\ x_{(2)} \le a$ and $\theta\, x_{(1)} + (1-\theta)x_{(2)} \ge a\}$. A bidding war occurs when $(x_{(1)},x_{(2)}) \in B = \{(x_{(1)},x_{(2)})|\ x_{(2)} \ge a\}$. 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 $\beta = \iint_B h_{(12)}(x_{(1)}, x_{(2)})dx_{(1)}dx_{(2)} = \int_a^{xH} h_{(2)}(x_{(2)})dx_{(2)}$, where $h_{(2)}(-)$ 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 $n \ge 2$, 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.

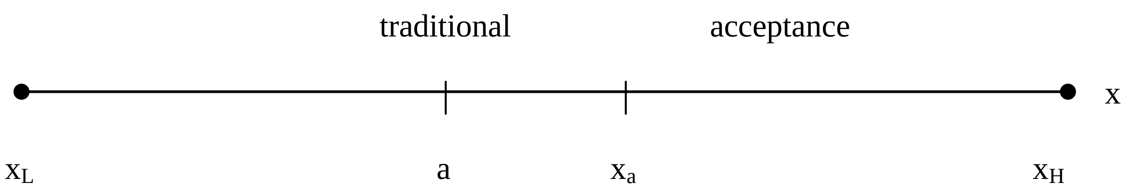
Despite the intractability, one can show that the key results from the discrete case continue to hold. The existence of three types of housing sale (Proposition 1) has already been established. It has also been established that the seller will use asking price to direct search at least by setting it 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 searches, 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.

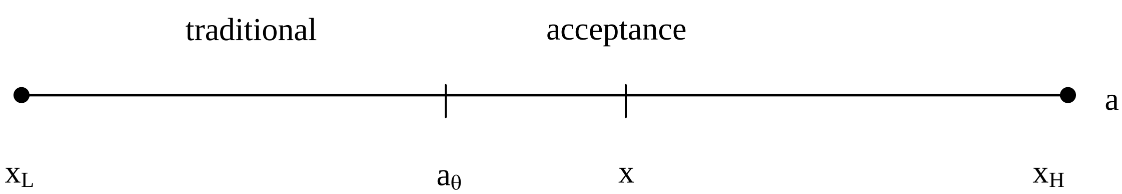
Figure A1. Acceptance and traditional cases with n=1

Panel (a): As a function of valuation.



Note:

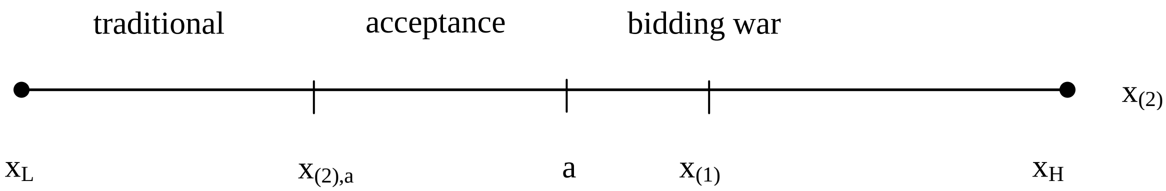
Panel (b): As a function of asking price.



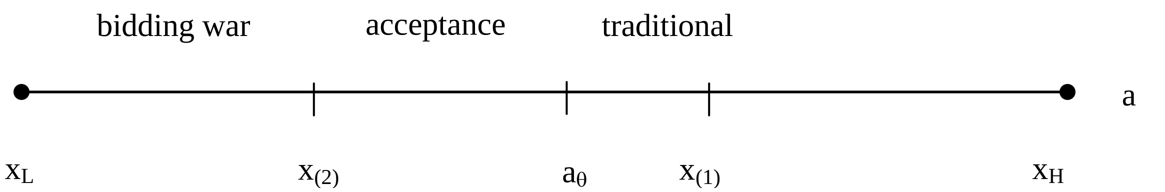
Note: This figure shows how asking price and valuation interact to determine transaction type when there is one visitor. Taking asking price as given, panel (a) maps values of x into the two possible sales cases, traditional below list sale and acceptance of the asking price. Taking x as given, panel (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 $x_{(1)} > a$.

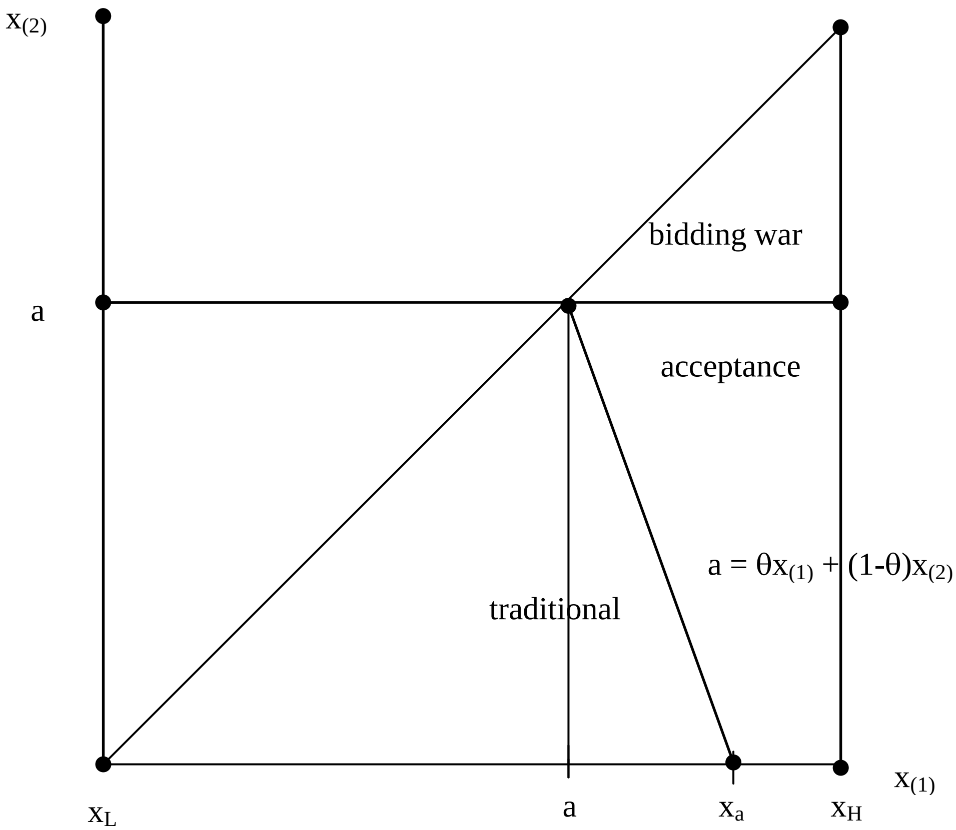


Panel (b): As a function of asking price, a.



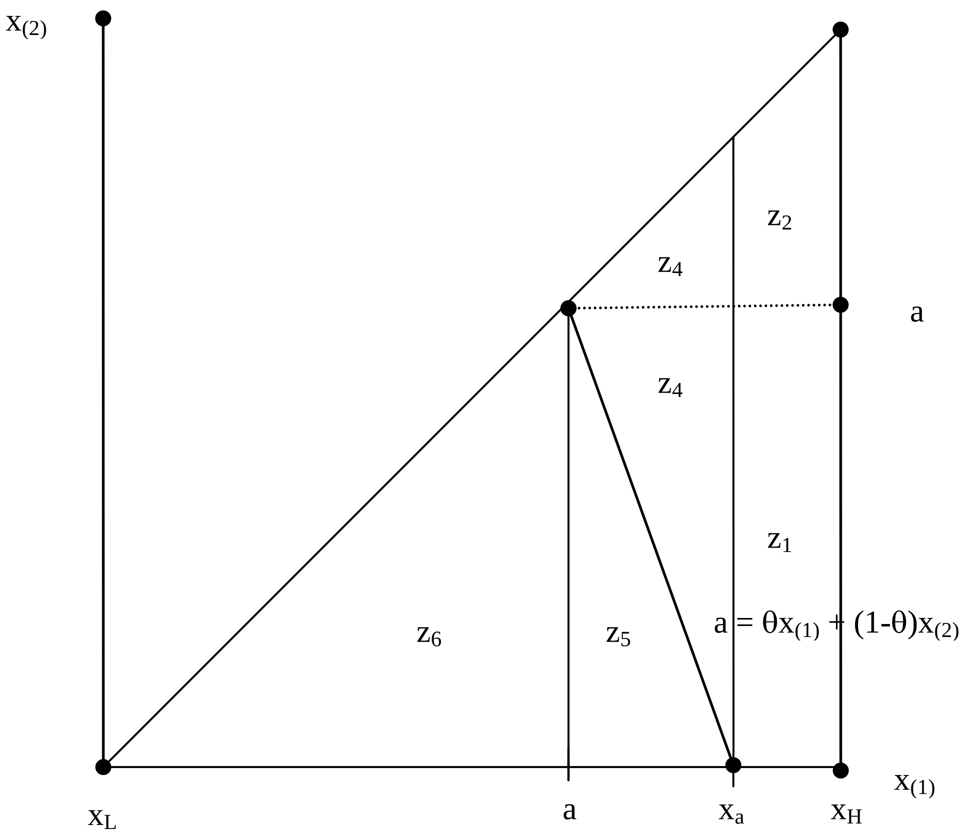
Note: This figure shows how asking price and valuation interact to determine transaction type with more than one visitor. Taking asking price and $x_{(1)}$ as given, panel (a) maps values of $x_{(2)}$ into the three possible sales cases, traditional below list sale, acceptance of the asking price, and 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.