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List Prices, Sale Prices and Marketing Time: An Application to U.S. Housing Markets

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Many goods are marketed after first stating a list price, with the expectation that the eventual sales price will differ. In this article, we first present a simple model of search behavior that includes the seller setting a list price. Holding constant the mean of the buyers' distribution of potential offers for a good, we assume that the greater the list price, the slower the arrival rate of offers but the greater is the maximal offer. This trade-off determines the optimal list price, which is set simultaneously with the seller's reservation price. Comparative statics are derived through a set of numerical sensitivity tests, where we show that the greater the variance of the distribution of buyers' potential offers, the greater is the ratio of the list price to expected sales price. Thus, sellers of atypical goods will tend to set a relatively high list price compared with standard goods. We test this hypothesis using data from the Columbus, Ohio, housing market and find substantial support. We also find empirical support for another hypothesis of the model: atypical dwellings take longer to sell.

Although the theory of how the seller of an asset searches for a buyer is well developed, it has focused less frequently on how list (ask) prices are determined. However, setting a list price that differs from the expected selling price is a common occurrence in the U.S. economy. One of the largest such examples is the housing market. In 2007, 6.43 million existing and new homes were sold, each having a seller-determined list price.[1] In the vast majority of cases, the list price exceeded the sales price. Setting a list price that differs from the expected sales price also is common for automobiles and the fine art market and it occurs in some Internet auctions.

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[1]See "U.S. Housing Market Conditions Spring, 2008" Tables 6 and 7 (HUD User 2008).

We first present a model that incorporates sellers setting list prices as part of their strategy. Next, we derive a hypothesis about which products are likely to have a higher ratio of list price to expected sales price, arguing that the ratio will be larger for goods where the variance of the distribution of buyers' offers is larger. We use data from the central Ohio housing market to test this hypothesis. The estimation results strongly support the model's predictions. Specifically, we find that the ratio of list price to expected sales price rises as the atypicality of a property increases. The model also predicts that the expected marketing time of a property increases with the amount of atypicality. The empirical results also support this hypothesis.

The next section of the article reviews the theoretical literature about list price determination, and it describes how we modify the optimal stopping rule model to include list prices. We then derive the model's testable hypotheses using a numerical model, focusing on a product's attributes' impact on list price. We also highlight the relationships between a product's characteristics and list price, expected sale price and marketing time. The fourth section describes our housing data set for the Columbus, Ohio, metropolitan statistical area (MSA). The empirical results are reported in the fifth section of the article, and we summarize the findings in the final section.

Theoretical Models of List Price Determination

DeGroot (1970) explicates optimal stopping rule strategies where a seller sets a reservation price and accepts the first offer that exceeds it. McCall (1970) applies this theory to labor markets, and Feinberg and Johnson (1977) demonstrate the extent of its superiority. The theory was adapted for the housing market by Haurin (1988). He showed that sellers of atypical properties, that is, ones with a greater variance in the buyers' offer distribution, will set their reservation price relatively high compared to the mean of the buyers' offer distribution. The hypothesized consequences are that the expected selling price of these atypical properties should be relatively high, as should the expected selling time. None of these early studies included list prices in the formal models.

A more recent set of articles introduced list prices into search models. Horowitz's (1992) model included many of the standard assumptions of the earlier literature such as sellers' reservation prices are unobserved and the seller knows the distribution of offers by potential buyers. He introduced two new assumptions to the model: the first is that the arrival rate of buyers is a decreasing function of the (time-invariant) list price, and the second is that buyers' bids do not exceed the list price. He derived the relationship between the seller's reservation price and list price, but he did not relate either price to the attributes of the buyers' offer distribution. Using a Baltimore housing sample, he finds that including list prices in a regression helps to explain sales price more accurately than just the set of property characteristics.

In Yavas and Yang's (1995) model, list prices form an upper bound for offers and also signal the market information about the seller's reservation price. Increasing the list price for a property reduces the likelihood of a seller–buyer match and the probability of a sale. Yavas and Yang also assume that the seller's broker's effort is related to the list price through the expected commission on the property. In their model, sellers, buyers and brokers pick the optimal search intensities, and the seller picks the list price. They hypothesize that an increased list price has an ambiguous effect on broker search effort and the expected marketing time of a property (holding constant property characteristics). However, they do not relate list price to the characteristics of the distribution of buyers' potential offers.[2]

A Model of Optimal List Price Determination

We present this model in order to more fully understand the impact of changing a set of exogenous variables on list prices and expected sales time. The exogenous variables include the variance of the distribution of potential buyers' offers, sellers' holding costs and a measure of the level of activity in the housing market. In particular, we look for a sense of whether responses to changes in the exogenous variables are linear or not.

The seller of an asset has the ability to set a list price, which we assume remains constant during the search. The seller then receives offers from potential buyers, these drawn from a known distribution. Each is considered in turn and either accepted, thereby stopping the search, or rejected, which continues the search. Offers, X_i, are independent, and there is no recall of rejected offers. The probability density functions associated with the X_i is described by $\phi(x)$. A seller's cost per unit of time spent waiting for an offer is time invariant.[3]

[2]Other theoretical models of list price determination include Green and Vandell (1994) and Arnold (1999). Neither study considers the impact of a property's characteristics on the variance of the buyers' offer distribution or the resultant impact on list prices. Arnold's (1999) study allows for bargaining between seller and buyer, and this model is then embedded within a search framework. His results regarding the relationship of list price and a seller's time rate of discount are similar to those of Yavas and Yang (1995). The problem with the analysis, other than its complexity, is that it does not yield any easily tested implications.

[3]The cost of selling likely differs among sellers. For evidence in the housing market, see Glower, Haurin and Hendershott (1998), who find that sellers have differing levels of motivation to sell. Thus, list price strategies are likely to differ among sellers.

We make two assumptions about the role of list prices in a seller's strategy. First, we assume that potential buyers who value a property at a level greater than the list price will make an offer no greater than the list price.[4] Thus, the list price is an upper bound on the sales price. Second, the greater the list price, holding constant the quality and quantity of the property, the lower the arrival rate of offers.[5] The justification for the first assumption is that, while overbidding on a product occurs occasionally, it is unusual. Also, it is likely that overbidding on properties is most frequent during a period of transition from a weak to stronger market; however, our model is applicable to situations where the market is in equilibrium.[6] The second assumption is that higher list prices convey, on average, higher quality. If a potential buyer views an overpriced property's characteristics either online or in person, the buyer is likely to be disappointed with the property's quality. Thus, we assume that the greater the ratio of the list price to the mean of the distribution of offer prices, the less likely is a random buyer to make an offer. For example, in the housing market real estate agents are aware of this type of buyer reaction to overpriced properties and may be less likely to exert effort to show an overpriced property to potential buyers. Both agent and buyer behaviors tend to reduce the arrival rate of offers. In summary, our assumptions result in a seller facing conflicting forces. A higher list price raises the truncation point of the buyers' distribution of offers, but it reduces the arrival rate of offers.

The model begins with the standard optimal stopping rule formulation, and Equations (1) to (4) below repeat this model. The seller maximizes net revenues on the sale of the asset and chooses both reservation and list price. Net revenues are the difference between the sales price and the time cost of holding the good. Let

R_n = net return from search at the time of the nth offer,
V_n = revenue at the time of the nth offer, given the value of the nth offer is X_n,
γ = cost per unit time of searching,
λ = list price and
$f(\lambda)$ = arrival rate of offers (offers per unit time).[7]

[4]This assumption, when applied to the housing market, results in the model being relatively more applicable to the United States than some other countries where the real estate market operates differently.

[5]We also assume that the list price is unchanged while the seller is waiting for an offer. This assumption simplifies the model considerably.

[6]In our housing data set, only 7.5% of properties that eventually sold had a sales price greater than the initial list price.

[7]More precisely, the arrival rate of offers is a function of the ratio of the list price to the mean of the distribution of potential offers.

Then $R_n = V_n - \frac{\gamma}{f} n$

and

$$E(R_n \mid n) = E(V_n \mid n) - \frac{\gamma}{f} n. \tag{1}$$

The seller's goal is to set a reservation price and list price such that $E(R_n \mid n.)$ is maximized. Designate N to be the first acceptable offer. Thus,

$$E(R_N \mid N) = E(X_N \mid N) - \frac{\gamma}{f} N, \tag{2}$$

where X_N is the value of Nth offer. Expecting out the N yields

$$E(R_N) = E(X_N) - \frac{\gamma}{f} E(N), \tag{3}$$

where $E(N)$ is the expected number of searches until an acceptable offer is received. The number of offers required for success is described by the geometric distribution: $P(N = n) = q^{n-1} p$, with $p =$ probability of success and $q = 1 - p =$ probability of failure.

$$E(N) = \sum_n n P(N = n) = \sum_{n=1}^{\infty} n q^{n-1} p = \frac{p}{(1-q)^2} = \frac{1}{p}.$$

The probability of success is $\rho = \int_{\varepsilon}^{\infty} \phi(t)\, dt$, where $\phi(t)$ is the distribution of offers by potential buyers. Thus,

$$E\,(N) = \frac{1}{\rho}. \tag{4}$$

$E(X_N)$ is the expected value of the accepted offer. The probability density function of X_N depends on the value of an offer compared with the seller's reservation price ε and, by the assumptions of our model, the list price.

$$\phi_{x_N} = \begin{cases} 0, \\ \dfrac{\phi(x_N)}{\rho}, \\ \dfrac{\int_{\lambda}^{\infty} \phi(t)\, dt}{\rho}, \\ 0. \end{cases} \tag{5}$$

In (5), there are four alternatives. The first occurs when an offer is less than the reservation price. In this case, the offer is rejected and thus $\phi_{x_N} = 0$. The second occurs when an offer is greater than or equal to the reservation price and less than or equal to the list price. In this case, the offer is accepted. If a potential offer exceeds the list price, then the offer tendered is the list price, by assumption. Finally, no offers exceed the list price. The expected value of the accepted offer is thus

$$E(X_N) = \frac{\displaystyle\int_{\varepsilon}^{\lambda} x_N \phi(x_N)\, dx_N + \lambda \int_{\lambda}^{\infty} \phi(t)\, dt}{\rho}. \tag{6}$$

Next, the seller maximizes the expected net return (3) with respect to the list price and reservation price. The first-order conditions are straightforward

$$\frac{\partial E(R_N)}{\partial \varepsilon} = 0 \text{ and} \tag{7a}$$

$$\frac{\partial E(R_N)}{\partial \lambda} = 0. \tag{7b}$$

The solution to (7a) yields an expression for the optimal reservation price

$$\varepsilon = \frac{\displaystyle\int_{\varepsilon}^{\lambda^*} x_N \phi(x_N)\, dx_N + \lambda^* \int_{\lambda^*}^{\infty} \phi(t)\, dt}{\rho} - \frac{\gamma}{\rho f(\lambda^*)}, \tag{8}$$

where λ^* is the optimal list price. In (8), the optimal reservation price is an implicit function of the list price, the expected waiting time and the frequency of offers.[8]

Combining (3) and (7b) yields

$$\frac{\partial E(R_N)}{\partial \lambda} = \frac{\partial E(X_N)}{\partial \lambda} + \frac{\gamma E(N)}{f^2}\frac{\partial f}{\partial \lambda} = 0. \tag{9}$$

Rewriting (9) yields

$$\frac{\partial}{\partial \lambda}\left[\frac{\displaystyle\int_{\varepsilon^*}^{\lambda} x_N \phi(x_N)\, dx_N + \lambda \int_{\lambda}^{\infty} \phi(x_N)\, dx_N}{\rho}\right] = -\frac{\gamma}{\rho f^2}\frac{\partial f}{\partial \lambda}. \tag{10}$$

The solutions for λ^* and ε^* are found from (8) and (10). We solve these numerically, and two assumptions are made to facilitate the solution. First, we introduce a specific functional form that relates the arrival rate to the list price

$$f(\lambda) = b - m(\lambda/\mu), \tag{11}$$

[8] That is, the reservation price equals the derivative of the expected net revenue function with respect to the reservation price.

where μ is the mean of the buyers' distribution of offers. In (11), the baseline arrival rate is b. The arrival rate falls the greater is the ratio of list price to the mean value of buyers' offers, with sensitivity parameter m. The second assumption is that the distribution of offers by potential buyers is normal with mean μ and variance σ^2. Given these assumptions, (10) can be simplified to (see the Appendix Part 1 for details)

$$1 - erf\left(\frac{\lambda - \mu}{\sigma\sqrt{2}}\right) = \frac{2\gamma m/\mu}{(b - m(\lambda/\mu))^2}, \tag{12}$$

where erf is the error function

$$erf(z) = \frac{2}{\sqrt{\pi}} \int_0^z e^{-\eta^2} d\eta. \tag{13}$$

In (12), we observe that λ^* can be determined given the parameters of the model and that it is independent of the reservation price. Thus, in the numerical solutions, we first solve for λ^* and then use (8) to solve for the optimal reservation price. We also note that the expected marketing time is the ratio of the expected number of offers to the frequency of arrival of offers: $E[N]/f$.

Of interest are the comparative static results that measure the responses of the reservation price, list price, expected marketing time and expected sales price to changes in the variance of the buyers' offer distribution. These hypotheses are applicable to the housing market where potential buyers' valuations of atypical properties likely have a much greater variance than standard track housing. A second application could be to the market for autos where "exotic" sports cars likely have a much larger variance of buyers' valuation compared with standard models. A third application is to the market for fine arts comparing the pricing strategy of controversial or avant-garde art to that for mainstream work.

The general direction of the effect of increased variance of the buyers' offer distribution is intuitively clear. The problem facing sellers of properties that have no variation in buyers' opinions is simple; they should set their reservation price and list price equal to the mean of the buyers' distribution of offers. Thus, they will accept the first offer, which by definition of this problem will be at the mean of the distribution. The sale will be quick and the return known. For example, one would expect that nearly identical houses in large subdivisions will have a list price quite close to their eventual sales price and that they will sell relatively quickly. This intuition also explains why the price on standardized goods (with very low variance of the buyers' distribution of offers) is not negotiable—their list price equals their expected sales price. In contrast, the owner of a product with a high variance of offers will set the list price above the mean of the buyers' distribution of offers. In general, intuition suggests that, holding constant property characteristics, the greater the variance of potential offers, the higher should be the list price, the expected sales price and the expected marketing time.[9]

A second series of comparative static results of interest are the responses to variations in holding costs during the search period. In the housing market, the response of marketing time to variations in a measure of sellers' level of motivation to sell was studied by Glower, Haurin and Hendershott (1998), who had access to private data about sellers while they were marketing their property. However, in general, sellers' holding costs are difficult to observe, making empirical tests impossible.

A number of other empirical studies have focused on list prices.[10] Genesove and Mayer (1997) argued that some homeowners are constrained by the amount of debt they have on a property and that this debt affects their reservation and list prices when selling. They used a sample of Boston condominiums and found that sellers with a relatively high loan-to-value ratio set a relatively high list price, *ceteris paribus*. Our sample does not contain information about the owner's equity in a home, and thus we cannot address this hypothesis.

Knight (2002) references Lazear's (1986) theory of multiperiod pricing with demand uncertainty to argue that the level of the initial list price affects the rate at which a seller learns about the buyers' distribution of offers. That is, setting a relatively high list price compared to the mean of the buyer offer distribution reduces the flow of potential buyers, resulting in fewer bids and less learning about the unknown properties of the bid distribution. Knight then argues that sellers of atypical properties, that is, ones sold in thin markets, should set a relatively low list price to encourage buyer arrivals resulting in more learning; however, he does not test this hypothesis. Assuming that atypical properties have a higher variance of potential buyers' distribution of offers, then this prediction stands in opposition to the one derived above where demand is certain. We note that setting a relatively low list price to encourage offers (and generate information) carries with it the cost of forgoing an offer from the upper tail of the buyer distribution, and we also note that information about the distribution of potential offers can be obtained from real estate agents and monitoring the level of seller interest in a property (*e.g.*, attendance at open houses).

[9]The latter two are expected values, and thus actual outcomes are subject to the luck of the draw in a sample.

[10]Examples include Anglin, Rutherford and Springer (2003), Knight, Sirmans and Turnbull (1994) (list price is a signal) and Merlo and Ortalo-Magné (2004) (in-depth description of list prices in the housing market).

Table 1 ■ Parameter and solution values for the baseline numerical simulation.

	Definition	Baseline Value
Parameter		
μ	Mean of buyers' distribution of offers	200,000
σ	Standard deviation of buyers' offers	4,000
b	Baseline arrival rate of offers per month	3
m	Sensitivity parameter: Attenuation of offers	1.8
c	Cost of waiting per month	1,000
Solutions		
λ^*	List price	209,770
ε^*	Reservation price	201,640
$E(X_N)$	Expected sales price	204,270
$E[N]/f$	Expected time on market (months)	2.638
$\lambda^*/E(X_N)$	Ratio of list price to expected sales price	1.027

Glower, Haurin and Hendershott (1998) do not present a model that includes list price determination. They conjecture that list price is lower for highly motivated sellers, but they do not test this hypothesis. In their list price estimation, they include an atypicality measure and find that the more atypical is the property, the higher is list price; this result is consistent with the model presented here.

Numerical Solutions

We solve the model using numerical methods. Once the model's parameter values are specified then the list price, expected sales price, reservation price and expected time on market can be determined. The baseline set of parameters and the solution to the model under these parameter values are listed in Table 1. For example, the ratio of list price to expected sale price is 1.027, and the expected marketing time is 2.64 months. Our focus is on how these values vary with the standard deviation σ of the distribution of offers by potential buyers. We vary the standard deviation of buyers' offers from 0% to 10% of the mean of the offer distribution and focus on the resulting changes in the ratio of the list price to the expected sales price.

We find that as σ rises from \$0 to \$20,000, the list price, expected sales price and reservation price rise. The expected marketing time rises from less than a month to about 9 months due to changes in the seller's strategy. The ratio of the list price to the expected sales price rises at a decreasing rate with increases in σ, this forming our first hypothesis. Thus, owners of atypical assets, that is, ones with a relatively large variance of opinions about its worth, will on average have a relatively high list price compared to the expected selling price. This

Table 2 ■ Variation in the baseline solution as parameter values change.

Parameter		List Price	Reservation Price	Expected Sales Price	List Price/ Sales Price	Time on Market
Cost per Month	250	211,590	204,750	206,690	1.024	7.763
	500	210,710	203,310	205,530	1.025	4.445
	1,000	**209,770**	**201,640**	**204,270**	**1.027**	**2.638**
	1,500	209,190	200,500	203,490	1.028	1.989
	2,000	208,750	199,600	202,900	1.029	1.652
b	2	202,320	193,830	199,780	1.013	5.949
	2.5	208,000	199,940	203,090	1.024	3.146
	3	**209,770**	**201,640**	**204,270**	**1.027**	**2.638**
	4	211,480	203,210	205,460	1.029	2.257
	6	213,080	204,620	206,600	1.031	1.977
m	0.1	215,390	203,920	206,040	1.045	2.116
	0.9	212,270	203,160	205,430	1.033	2.274
	1.8	**209,770**	**201,640**	**204,270**	**1.027**	**2.638**
	2.3	207,490	199,840	203,000	1.022	3.158
	2.8	200,980	193,570	199,240	1.009	5.674

Note: The baseline cases are in bold.

latter result implies these owners will agree to a relatively large discount from their list price, but they still sell for a higher price than a more typical property with the same mean valuation. We also find that the expected marketing time increases approximately linearly with the variance of the distribution of buyers' offers, this forming our second hypothesis.

The impact of variations in the model's parameter values on the baseline case are displayed in Table 2. As the cost per month of waiting for an offer rises, the list and reservation prices fall, with the reservation price falling at a slightly greater rate. The result of reducing the reservation price is to accept an offer earlier in the search, and thus the expected marketing time falls substantially. These predictions are consistent with casual observations that sellers with a high urgency to sell (*e.g.*, a home seller has bought another property contingent on the sale of the current home) set the reservation price relatively low, even below the mean of the distribution of buyers' offers. Interestingly, greater holding costs result in only modest reductions in list prices. The low reservation price tends to result in a quick sale, but buyers cannot take advantage because it is unobservable. The small reduction in list price increases the frequency of offers by a small amount, and it only modestly reduces the maximal offer. That is, the modest list price reduction yields little information about the seller's high level of motivation to sell. In contrast, sellers who are testing the water presumably are characterized by having a low holding cost. The result is that they set the list price and reservation prices relatively high and tend to wait a long time for an acceptable offer.

The arrival rate of offers is described in Equation (11), and it depends on both b and m. The parameter b can be interpreted as reflecting the overall strength of the market, be it boom or bust. During time periods or in locations where the baseline arrival rate (b) is high, the seller sets a relatively high list and reservation price, and the ratio increases with b.[11] Even with these higher price levels, the expected marketing time is reduced due to the relatively high arrival rate of offers. At the other extreme, when offers arrive infrequently, such as when $b = 2$ (with $m = 1.8$), sellers reduce list price to below the mean of the sellers' distribution of offers, and even with this action expected marketing time is about 6 months. In the baseline case, the expected sales price is \$204,270, while in this down market case it falls to \$199,780.[12]

A third set of variations occurs when there are changes in m, the sensitivity parameter. Changes in m have two effects: increased m reduces the arrival rate of buyers similar to the effect of reducing b, and increased m decreases the incentive to set a list price above the buyers' mean valuation. As m rises both of these effects work to lower the list price, causing the ratio of the list price to the expected selling price to fall substantially. For small values of m, the seller is less concerned about diminishing the arrival rate of buyers and thus raises the list price substantially. In the extreme, when $m = 0$, there is no effect of list prices on the arrival rate of offers, and the optimal list price is infinite.[13] In this case, the reservation price is set in the same way as in a model where list price is excluded from the analysis.

These variations in expected sale price raise the question of the definition of the true value of the asset, the answer important for property appraisals. One definition is that value equals the expected sale price for the average seller in a

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[11]For example, the rate of sales of existing homes to that of the stock of owner-occupied housing has varied from 4.0% to 9.4% during the period 1970–2005 (HUD 2008, Tables 7 and 25). The peak sales years were in the late 1970s and 1999–2005, and the trough years occurred in 1970–1975 and 1981–1985.

[12]The prediction that the discount from list price is larger in a strong market appears counterintuitive. Note, however, that these comparative predictions are made in a model where equilibrium has been achieved in a stable market. During a period of dynamic change, such as when the arrival rate of buyers is rising, a different prediction would occur; specifically, the discount would be relatively low.

[13]In Equation (11) the right-hand side equals 0, requiring $erf(\frac{\lambda-\mu}{\sigma\sqrt{2}}) = 1$, which occurs when the list price is infinite.

typical time period. This could be restated in this model as requiring that b, c and m be "typical." The expected sales price likely differs from the observed transaction price, which is determined in part by the luck of the draw. A much different value would be identified if the definition of value was the mean of the buyers' distribution of offers (constant at $200,000 in Table 2). But this value is invariant to changes in σ, which would eliminate any impact of normal optimizing search behavior on value.

Data

We test two of the hypotheses generated by the model of optimal list price determination; specifically, that the ratio of the list price to the expected sales price is greater, and marketing time is greater the larger is the variance of the distribution of buyers' offers. To implement these tests, we must address two measurement issues. The first is how to measure the variance, and the second is the measurement of the expected sales price.

For the variance, we create a variable that measures the atypicality of an asset, the assumption being that the diversity of opinions about the value of an asset is greater the more unusual is the asset. Our application is to housing, and the measure of atypicality of a house uses market information to create a dollar-denominated measure of how different a property is compared with other housing in the local submarket.

The atypicality measure (A) for the ith property in the jth jurisdiction is defined as

$$A_{ij} = \sum_k p_k |h_{kij} - \bar{h}_{kj}|, \tag{14}$$

where the h_{kij} are the characteristics of a property, $\bar{h}_{jk}$ is the mean value of the kth characteristic in the jth suburb and the p_k are the implicit prices of the property's characteristics. Thus, the atypicality variable measures the dollar value of the absolute value of the deviations from the submarket mean of a property's characteristics. The implicit prices of the characteristics are derived from a hedonic house price regression that relates transaction prices to a set of house characteristics. The table in the Appendix presents the hedonic estimation for one of the suburbs (Dublin, Ohio) as an example of the method. The atypicality variable is created for each jurisdiction in our sample for multiple reasons. A single measure for the entire MSA would clearly mix together submarkets where the characteristics of the typical house differ. An advantage of using suburban jurisdictions is that their boundaries are exogenous, which would not be true if we defined atypicality at the neighborhood level. Another rationale is that buyers tend to search for houses within a jurisdiction, in part because of the correspondence of public school districts with suburban boundaries.

Measuring the ratio of list price to expected selling price requires addressing the issue that some properties are listed for sale but do not sell. The numerator of the ratio is observed for all properties, but sales price is not observed for unsold properties. We estimate the expected sales price of properties by using the hedonic house price estimation method, where for each submarket the sales price of sold properties is regressed on a vector of house characteristics. These estimated implicit market prices of house characteristics are then applied to the set of unsold houses, and their expected sales price is estimated. Because the sample of sold properties may be selective, we first estimate a probit model of whether a house sold or not during the period, then we create the sample selection correction variable (inverse Mills' ratio), which is then inserted into the hedonic price estimation (Heckman 1979). We use the resulting set of unbiased implicit prices to estimate the expected sales price of all properties including those which did not sell. It is important to include listed but unsold properties in the sample because, as noted above, atypical properties are expected to have the longest marketing times and thus be the least likely to sell during any particular period.

Because the ratio of list to sales price also varies with b and m, which are likely to systematically vary over time depending on the strength of the housing market, we include a set of year and seasonal dummy variables in the estimation. If a measure of the seller's cost of holding a property was available, it also should be included, but our data set does not include any measures of holding cost.

Our data set is drawn from the Multiple Listing Service (MLS) records for central Ohio (the Columbus metropolitan area) from 1997 to 2005. The data contain a listing's initial list price, house characteristics, time on market (all properties) and the sales price (if sold) for all houses listed in the MLS.[14] The metropolitan area includes eight suburban jurisdictions, each comprising two ZIP codes on average, which have a sufficient number of transactions so that hedonic estimation methods can be applied. We exclude central city transactions because that market is so large and diverse that it is difficult to identify atypical houses. In contrast, the suburban markets are relatively homogeneous, although somewhat different from each other. In Table 3 , Panels A and B present a summary of the mean sale, list price and constructed measure of atypicality for each jurisdiction. The mean atypicality measure is smaller in the newer suburbs (Hilliard, Pickerington) where the new construction tends

[14]In Columbus, only a small percentage of houses are sold, but not MLS listed, such as those "for sale by owner." In our data set, buyers' offers are not observed.

Table 3 ■ Means and standard deviations for eight suburban samples.

Panel A: Total Sample Summary Statistics

	Total Obs.	Sold Obs.	% Sold	List Price Mean	List Price Std. Dev.
Aggregate	47,590	34,846	73.2%	242.5	186.9
Bexley	2,731	1,997	73.1%	286.4	238.4
Dublin	8,248	5,855	70.9%	320.5	217.4
Gahanna	6,085	4,639	76.2%	198.7	141.2
Hilliard	5,637	4,055	71.9%	200.8	110.2
Pickerington	8,563	5,533	64.6%	200.9	160.7
Upper Arlington	6,814	5,330	78.2%	307.4	240.3
Westerville	6,824	5,277	77.3%	201.1	139.5
Worthington	2,688	2,160	80.4%	217.8	133.9

Panel B: Sold Sample Summary Statistics

		Mean			Std. Dev.		
	Obs.	Sold Price	List Price	Atypicality	Sold Price	List Price	Atypicality
Aggregate	34,846	214.7	222.7	66.8	124.9	134.5	82.5
Bexley	1,997	243.8	258.5	118.1	167.7	185.1	101.8
Dublin	5,855	283.9	293.3	95.5	137.9	144.6	88.4
Gahanna	4,639	179.6	184.7	52.5	94.7	98.8	51.4
Hilliard	4,055	182.9	188.4	23.2	94.3	99.4	21.8
Pickerington	5,533	176.6	181.6	33.2	75.7	79.9	60.2
Upper Arlington	5,330	262.6	277.0	121.2	168.5	187.8	114.2
Westerville	5,277	181.9	187.0	51.8	78.2	81.7	53.1
Worthington	2,160	194.8	202.4	42.9	89.4	96.8	65.1

Panel C: Relationship of Atypicality (by Decile) and the List-Price-to-Sales-Price Ratio

Decile	Average Atypicality	List Price/Sale Price
0-10	6,921	1.026
11-20	18,635	1.027
21-30	31,798	1.030
31-40	45,308	1.030
41-50	58,431	1.031
51-60	72,316	1.032
61-70	89,284	1.032
71-80	113,749	1.034
81-90	158,765	1.038
91-100	563,505	1.049

Table 3 ■ continued

Panel D: Time on Market Summary Statistics

	Total Sample			Sold Sample		
	Obs.	Mean No. of Days	Std. Dev. No. of Days	Obs.	Mean No. of Days	Std. Dev. No. of Days
Aggregate	47,590	89.8	97.0	34,386	71.8	82.4
Bexley	2,731	100.4	102.2	1,997	83.4	91.9
Dublin	8,248	98.5	111.5	5,855	78.0	92.6
Gahanna	6,085	84.6	91.7	4,639	69.1	76.8
Hilliard	5,637	85.1	89.6	4,055	67.7	76.2
Pickerington	8,563	104.9	98.5	5,533	83.2	85.8
Upper Arlington	6,814	81.6	96.3	5,330	66.7	83.1
Westerville	6,824	78.7	84.1	5,277	64.3	71.0
Worthington	2,688	74.6	87.7	2,160	60.3	75.9

Notes: All prices are in thousands of dollars. Panel A presents summary statistics for the entire sample. Panel B reports summary statistics for homes that sold. Panel C reports the mean ratio of list to sales prices for ten deciles of the distribution of atypicality. Panel D reports time on market summary statistics. The sample is from 1997 to 2005.

to be relatively uniform, while it is larger in the older established suburbs of Bexley and Upper Arlington. Panel A reports the data for the full sample and Panel B for the sample of sold properties.

Although the hypothesis that relates atypicality to the ratio of list to selling price will be tested at the level of individual houses, we also test it across communities based on the data in Table 3. First, we construct the ratio of mean list price to sales price in the sold property sample and then correlate it with the mean value of atypicality of houses in the community, yielding a correlation of 0.82. This high positive correlation is consistent with our hypothesis that the greater the amount of atypicality, the greater the ratio of list to sales price. This relationship also can be seen by noting how the average ratio of list to sales price varies with the deciles of the atypicality measure for the market. Panel C shows that the list-to-sales-price ratio increases monotonically as the atypicality measure rises from decile to decile.

Panel D of Table 3 reports marketing time summary statistics by community. Overall, the time on market of properties was about 90 days; it was shorter for the sold sample (72 days). Variation among communities ranged from 75 to 105 days.

Results

The primary hypothesis is that the ratio of the list price to the expected sales price of a property rises the greater is the variance of the distribution of buyers' offers as measured by our index of atypicality. In Tables 4 and 5, we present regression results for the eight suburbs and the aggregation of these suburbs, both with and without year and quarter dummy variables. As noted earlier, there is a choice of the method of valuing the expected sales price. In Table 4, we limit the sample to homes that sold and use the actual sales price as the value of the expected sales price. The left panels of results exclude time dummy variables, while the right panels include them. Throughout the results, inclusion of the time dummies has little effect on the signs or significance of the atypicality variable. In Panel A, we use the sample selection correction method to calculate the hedonic price equation's coefficients that are used to calculate the atypicality measure. In Panel B, we use the coefficients from a simple hedonic estimation.

Our empirical measure of atypicality is a generated regressor. As a result, the standard errors and test statistics obtained from the regression are generally invalid because they ignore the sampling variation in the factors used to generate the estimate of the variable in the first-stage equation (Woolridge 2000). We correct for this problem in the estimates reported in Tables 4–6 by bootstrapping our standard errors as a means of obtaining a description of the sampling properties of our empirical estimators using the sample data themselves (Greene 2003).

The numerical solutions and sensitivity tests suggested that the greater a property's atypicality, the higher the list-price-to-expected-sales-price ratio. The numeric model suggested that the relationship should be nonlinear, with the price ratio rising at a decreasing rate as the variance rises. Our preferred results of Table 4 are in the right side of Panel A. We find the results are generally supportive as the coefficient of atypicality is always positive, while its square is negative and significant in the aggregate estimation. However, the results regarding the curvature are not significant in the community regressions.

Table 5 follows a similar format, except now the sample is expanded to contain all listed houses, a superior approach compared with dropping unsold properties. The results in Panel A are based on calculating the expected sales price using the Heckman-corrected implicit price characteristics, while those in Panel B are not. The most preferred specification is in Table 5, Panel A, right side, which contains the time period dummy variables. We find that atypicality has a positive, but diminishing effect on the price ratio. Negative and significant effects for atypicality squared are found for four of eight suburbs. In one

Table 4 ■ Nonlinear estimation of the relationship of the ratio of list price to actual sales price with atypicality.

	Without Time Dummy Variables				*With Time Dummy Variables*			
Panel A	Constant	Atypicality	Atypicality^2	Adj. R^2	Constant	Atypicality	Atypicality^2	Adj. R^2
Aggregate	1.03***	1.05e-07***	−1.47e-14**	0.03	1.03***	1.01e-07***	−1.37e-14***	0.06
	[2933]	[19.52]	[−2.16]		[1159]	[18.55]	[−3.33]	
Bexley	1.04***	7.57e-08	3.41e-14	0.03	1.03***	6.86e-08	3.86e-14	0.06
	[257]	[1.55]	[0.34]		[162]	[1.43]	[0.42]	
Dublin	1.03***	1.75e-08	8.62e-14***	0.03	1.03***	1.05e-08	9.84e-14***	0.04
	[1156]	[1.50]	[3.56]		[619]	[0.78]	[3.20]	
Gahanna	1.02***	6.56e-08***	−6.33e-15	0.01	1.03***	4.43e-08**	4.93e-14	0.04
	[1223]	[3.30]	[−0.08]		[567]	[2.21]	[0.62]	
Hilliard	1.02***	9.44e-08***	4.64e-14	0.03	1.02***	8.70e-08**	5.58e-14	0.06
	[873]	[3.16]	[0.34]		[415]	[2.51]	[0.33]	
Pickerington	1.02***	9.84e-08***	−1.57e-14	0.01	1.02***	7.94e-08**	−1.24e-14	0.04
	[1047]	[3.26]	[−0.12]		[563]	[2.05]	[−0.07]	
Upp. Arlington	1.04***	8.17e-08***	−2.04e-15	0.02	1.04***	7.35e-08***	2.88e-16	0.07
	[471]	[3.45]	[−0.06]		[289]	[2.62]	[0.01]	
Westerville	1.02***	7.47e-08***	−2.68e-14	0.01	1.02***	6.78e-08***	−2.28e-14	0.04
	[1170]	[4.41]	[−0.85]		[562]	[4.02]	[−0.52]	
Worthington	1.03***	7.31e-08	−1.00e-14	0.01	1.03***	6.33e-08	−6.18e-15	0.04
	[491]	[1.22]	[−0.04]		[290]	[1.23]	[−0.02]	

Table 4 ■ continued

Panel B	*Without Time Dummy Variables*				*With Time Dummy Variables*			
	Constant	Atypicality	Atypicality^2	Adj. R^2	Constant	Atypicality	Atypicality^2	Adj. R^2
Aggregate	1.03***	1.09e-07***	−1.38e-14*	0.04	1.02***	1.06e-07***	−1.26e-14**	0.06
	[2710]	[18.72]	[−1.81]		[1165]	[20.22]	[−1.99]	
Bexley	1.04***	4.18e-08	1.17e-13	0.03	1.03***	3.97e-08	1.18e-13	0.06
	[314]	[0.85]	[0.99]		[145]	[0.75]	[0.99]	
Dublin	1.03***	1.78e-08*	9.71e-14***	0.03	1.03***	9.87e-09	1.11e-13***	0.04
	[1333]	[1.67]	[3.74]		[559]	[0.72]	[3.45]	
Gahanna	1.02***	6.97e-08***	5.77e-15	0.01	1.03***	4.68e-08**	7.16e-14	0.04
	[1028]	[2.98]	[0.06]		[517]	[2.10]	[0.80]	
Hilliard	1.02***	2.82e-07***	1.37e-13	0.03	1.02***	2.44e-07***	2.45e-13	0.06
	[1202]	[5.26]	[0.26]		[505]	[5.28]	[0.74]	
Pickerington	1.02***	1.27e-07***	−3.01e-14	0.01	1.02***	1.07e-07*	−2.49e-14	0.04
	[894]	[2.67]	[−0.11]		[528]	[1.90]	[−0.06]	
Upp. Arlington	1.04***	7.84e-08***	−1.30e-15	0.03	1.04***	7.05e-08***	9.66e-16	0.07
	[561]	[3.92]	[−0.06]		[278]	[2.73]	[0.02]	
Westerville	1.02***	7.05e-08***	−1.49e-14	0.01	1.02***	6.23e-08***	−7.09e-15	0.04
	[1102]	[4.26]	[−0.39]		[557]	[3.63]	[−0.27]	
Worthington	1.03***	9.77e-08	−1.65e-14	0.01	1.03***	8.69e-08	−9.84e-15	0.04
	[440]	[1.01]	[−0.02]		[254]	[0.99]	[−0.01]	

Notes: Panel A of the table reports the ordinary least squares estimates obtained from a regression of the ratio of list price to expected sales price on the atypicality measure, where the expected sales price is equal to the actual sales price if the home sold. Homes that listed but did not sell are excluded. We report results with and without year and quarter dummy variables and suburb-specific dummy variables for the years 1997–2005. Panel B employs the same specification as Panel A, but the atypicality variable is calculated without Heckman-corrected coefficients on each of the atypicality inputs. See the Appendix for an explanation of the construction of the atypicality variable. This table also includes atypicality squared in the specification, a test of nonlinearity in atypicality. The sample is from 1997 to 2005.

*, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 5 ■ Nonlinear estimation of the relationship of the ratio of list price to expected sales price with atypicality.

	Without Time Dummy Variables				*With Time Dummy Variables*			
Panel A	Constant	Atypicality	Atypicality^2	Adj. R^2	Constant	Atypicality	Atypicality^2	Adj. R^2
Aggregate	0.97***	4.01e-07***	−9.17e-14***	0.01	0.96***	3.95e-07***	−9.05e-14***	0.01
	[405]	[12.22]	[−2.79]		[142]	[13.82]	[−2.95]	
Bexley	0.78***	7.43e-07***	−3.84e-13**	0.04	0.68***	8.11e-07***	−4.81e-13**	0.14
	[59.73]	[5.92]	[−2.05]		[30.64]	[5.54]	[−2.27]	
Dublin	0.93***	2.14e-07**	1.24e-13	0.02	0.88***	2.12e-07***	1.24e-13	0.02
	[134]	[1.97]	[0.57]		[87.82]	[2.89]	[1.01]	
Gahanna	0.84***	1.02e-06***	−9.47e-13	0.02	0.78***	9.30e-07***	−7.13e-13	0.05
	[96.26]	[4.97]	[−1.07]		[46.85]	[5.54]	[−1.11]	
Hilliard	0.77***	2.53e-07***	8.03e-13**	0.03	0.59***	2.03e-07***	7.86e-13**	0.40
	[198]	[2.83]	[2.19]		[63.50]	[2.76]	[2.07]	
Pickerington	1.06***	1.46e-06***	−2.59e-13	0.04	1.14***	1.47e-06***	−2.62e-13	0.07
	[64.45]	[2.84]	[−0.13]		[60.93]	[2.97]	[−0.14]	
Upp. Arlington	1.03***	6.90e-07***	−2.83e-13***	0.02	1.14***	7.09e-07***	−2.89e-13***	0.03
	[135]	[7.89]	[−3.13]		[44.59]	[8.08]	[−3.68]	
Westerville	1.03***	7.33e-07***	−2.03e-12***	0.01	1.06***	7.06e-07***	−1.92e-12***	0.01
	[218]	[5.65]	[−3.23]		[103]	[5.32]	[−3.50]	
Worthington	1.01***	1.03e-06***	−1.39e-12***	0.03	1.05***	1.03e-06***	−1.39e-12***	0.03
	[137]	[7.91]	[−3.39]		[53.89]	[6.25]	[−3.10]	

Table 5 ■ continued

	Without Time Dummy Variables				*With Time Dummy Variables*			
Panel B	Constant	Atypicality	Atypicality^2	Adj. R^2	Constant	Atypicality	Atypicality^2	Adj. R^2
Aggregate	1.02***	5.78e-07***	−2.17e-13***	0.01	1.06***	5.81e-07***	−2.17e-13***	0.01
	[384]	[12.20]	[−4.89]		[82.63]	[9.86]	[−4.18]	
Bexley	0.92***	1.87e-06***	−1.94e-12***	0.05	1.06***	1.92e-06***	−1.99e-12***	0.07
	[56.33]	[8.13]	[−4.81]		[22.94]	[8.43]	[−5.12]	
Dublin	1.03***	3.43e-07***	2.3e-14	0.02	1.07***	3.49e-07***	1.72e-14	0.02
	[171]	[4.21]	[0.16]		[87.74]	[4.22]	[0.11]	
Gahanna	0.98***	1.68e-06***	−2.66e-12**	0.02	1.04***	1.68e-06***	−2.65e-12**	0.03
	[111]	[6.93]	[−1.97]		[51.96]	[5.98]	[−2.05]	
Hilliard	1.04***	2.62e-07	3.21e-12	0.01	1.06***	2.82e-07	2.98e-12	0.01
	[198]	[0.78]	[0.82]		[87.18]	[0.79]	[0.70]	
Pickerington	1.01***	1.42e-06***	−4.03e-13	0.03	1.05***	1.41e-06***	−4.03e-13	0.03
	[84.70]	[2.84]	[−0.15]		[61.00]	[2.79]	[−0.15]	
Upp. Arlington	1.01***	5.68e-07***	−2.31e-13**	0.01	1.06***	5.84e-07***	−2.36e-13**	0.01
	[71.76]	[3.39]	[−2.24]		[16.27]	[3.16]	[−2.12]	
Westerville	1.02***	6.91e-07***	−1.72e-12***	0.01	1.04***	6.66e-07***	−1.63e-12***	0.01
	[273]	[6.32]	[−3.01]		[96.40]	[5.61]	[−2.84]	
Worthington	1.01***	9.78e-07***	−2.82e-12***	0.01	1.04***	9.79e-07***	−2.85e-12***	0.01
	[126]	[4.67]	[−2.85]		[54.55]	[4.59]	[−3.50]	

Notes: This table reports the ordinary least squares estimates of a regression of the list-price-to-expected-sales-price ratio on the atypicality measure. Expected sales price is estimated for each property in the sample using a hedonic pricing equation. Panel A reports the results when expected sales price and atypicality are computed using a Heckman-corrected equation. Panel B reports results without the Heckman correction in either of the expected sales price or atypicality measures. This table also includes atypicality squared in the specification, a test of nonlinearity in atypicality. The sample is from 1997 to 2005.

Table 6 ■ Estimates of time on market and atypicality.

	Aggregate	Bexley	Dublin	Gahanna	Hilliard	Pickerington	Upp. Arlington	Westerville	Worthington
Atypicality	−1.41e-06***	−1.59e-06***	−6.35e-07**	−3.50e-07	2.02e-06**	−1.06e-06	−1.19e-06***	−4.23e-07	−1.77e-06
	[−7.63]	[−3.13]	[−2.07]	[−0.55]	[2.45]	[−0.77]	[−3.16]	[−0.91]	[−1.03]
Atypicality2	2.60e-14	1.70e-13	−2.21e-12***	−6.13e-12**	−1.46e-11***	5.19e-14	2.15e-14	−7.73e-13	2.33e-13
	[0.06]	[0.20]	[−2.68]	[−2.15]	[−3.89]	[0.01]	[0.03]	[−0.43]	[0.028]
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Suburb dummies	Yes	No	No	No	No	No	No	No	No
Observations	46,303	2,718	8,178	6,051	4,793	8,418	6,747	6,787	2,611
No. of failures	33,800	1,984	5,788	4,606	3,436	5,395	5,264	5,240	2,087
Log Likelihood	−334,659	−13,949	−47,300	−36,233	−26,300	−44,376	−41,902	−41,810	−14,672
$Prob > x^2$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The Cox proportional hazard model estimates the probability of a home selling in the next period (day) given that the home has not yet sold. The sample period runs from 1997 to 2005. Atypicality is calculated using a Heckman-corrected equation. The table reports β_x, not hazard ratios.

(Hilliard), the result suggests that the list-to-expected-sales-price ratio rises at an increasing rate with atypicality.

To interpret the size of the effect, consider the marginal effect of increasing a house's level of atypicality from $0 to $67,000 on the list-price-to-sales-price ratio. (Table 3 reports the aggregate mean value of atypicality is about $67,000, with a standard deviation of $82,000.) In the aggregate sample (Table 5, Panel A), this increase in atypicality raises the price ratio by 0.026, that is, list price increases by about 3%. Given that the sample average list price exceeds the sales price by 3.7%, the effect of atypicality on the price ratio is substantial. The range of the marginal effect of the same $67,000 increase in atypicality ranges from 1.4% to 9.8% among the suburbs, but it is likely that much of this intersuburb variation is due to the smaller sample sizes.

Table 6 reports the results of the analysis of the marketing time of properties. We use a proportional hazards model and report the estimated coefficients. All properties for which we have marketing time data (sold and unsold) are included in the sample.[15] A negative coefficient indicates that the explanatory variable decreases the probability of the event (a sale) and thus increases marketing time. In the aggregate sample, we find that atypicality has a negative coefficient, while that of its square is positive but not significant. The implication is that dwellings with greater atypicality have a longer marketing time, but that the effect may decrease with increased atypicality. In the eight community regressions, atypicality has a clear negative effect in three, with four cases being insignificant. In the other community (Hilliard), the combined effects of atypicality and its square becomes negative at values above $67,000. To consider the economic significance of the results for the aggregate sample, a one-standard-deviation change in atypicality equals $82,500. Comparing two dwellings, one with a one-standard-deviation-greater level of atypicality would have a 10.9% lower probability of sale.

We next consider issues dealing with the robustness of our results. Our primary measure of atypicality monetizes the differences in attributes of each home, without adjusting for the effects of atypicality on the homes' own prices (Dumbrow, Sirmans and Turnbull 2006).[16] In order to address this concern, we construct an alternative measure of atypicality using only data on the house size (measured using square feet), where atypicality is defined as deviations from the community's average size. We rerun the tests and find that our main results

[15]Including unsold properties obviously is superior to omitting unsold properties. Unsold properties, for example, those withdrawn from the market, are treated as censored observations.

[16]We thank an anonymous referee for pointing this out.

are robust to this alternative measure. In order to address concerns that our results may be driven by substantial right skewness in our atypicality measure, we calculate log-atypicality and rerun the tests. Again, our results are robust to this alternative measure of atypicality. Finally, we consider the possibility that a neighborhood with a bimodel distribution in the style of homes could result in average characteristics that would make each home in the sample appear atypical even though each of the modal houses could be considered typical.[17] Unreported summary statistics for each suburb confirm that our data do not suffer from this problem.

Conclusions

List prices differ from sales prices in many markets. This article uses search theory to consider how sellers will optimally set list price, as well as their reservation price. We assume that list prices have two effects on the search process. One is that the list price establishes an upper limit on buyers' offers, and the other is that list price affects the arrival rate of offers.

We argue that sellers' search behaviors depend on the variance of the distribution of buyers' potential offers for a property. We show that the greater the variance of the offer distribution, the higher a seller will set list and reservation price. We also show that the ratio of list price to reservation price rises with the variance, as does the ratio of list price to expected sales price. The latter ratio is of special interest because list prices and sales prices are observable, and thus this hypothesis can be tested if a measure of the variance of buyers' offers can be constructed.

Applications of this theory are to any market where setting a list price that is expected to be negotiated is commonplace. A major application is to the U.S. housing market. We use a Columbus, Ohio, housing data set to test the model's hypothesis that the ratio of the list to expected sales price increases at a decreasing rate with increases in the variance of buyers' distribution of potential offers. We argue that this variance can be measured by the atypicality of a property. In samples drawn from eight separate suburbs, we find confirmation that increased atypicality raises the ratio of list to sales price, but at a decreasing rate. The model also predicts that the marketing time of atypical properties will be greater than for those that are relatively typical. Again, we find evidence consistent with this hypothesis in the Columbus sample.

A number of other interesting observations are derived from the numerical analysis of list price determination. The owners of highly atypical properties

[17] We thank an anonymous referee for pointing this out.

set list price relatively high, but they also tend to offer buyers relatively high discounts from list price. Sellers with a low holding cost set a relatively high list price, but not extraordinarily high. The reason is that they do not want to substantially reduce the arrival rate of offers. Interestingly, sellers with a high urgency to sell (high holding cost) do not set a low list price; rather, they set a low reservation price. This strategy is sensible because the high list price does not eliminate high offers from buyers who have a relatively high valuation of the property, while the low reservation price (which is unobservable) yields a quick sale. In markets or time periods where there is a high arrival rate of buyers, sellers set list prices relatively high, and we predict that the ratio of list to expected sales price will be high. Thus, during stable strong periods of sales, one would expect, counterintuitively, that sellers' discounts from list prices will be relatively high. The discounts will be smaller during stable down markets due to the much lower list price adopted by the seller.[18] Finally, as the sensitivity of the arrival rate to relatively high list prices (overpricing) increases, sellers set lower list prices to attempt to maintain the flow of buyers' offers.

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[18]These statements do not hold during the period of transition from boom to bust or vice versa. A dynamic model is required for these transitional periods when sellers may be "surprised" by changes in the arrival rate of buyers.

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Appendix

Part 1: Derivation of Equation (12)

Equation (10) is $\frac{\partial}{\partial\lambda}[\frac{\int_{\varepsilon^*}^{\lambda} x_N\phi(x_N)\,dx_N+\lambda\int_{\lambda}^{\infty}\phi(x_N)\,dx_N}{\rho}] = -\frac{\gamma}{\rho f^2}\frac{\partial f}{\partial\lambda}$.

It simplifies to

$$0 = \lambda\phi(\lambda) + \int_{\lambda}^{\infty}\phi(x_N)\,dx_N - \lambda\phi(\lambda) + \frac{\gamma}{\rho f^2}\frac{\partial f}{\partial\lambda}. \tag{A.1}$$

Inserting our assumptions about the normality of buyers' offer distribution and the response of the arrival rate to variations in list price (where $\frac{\partial f}{\partial\lambda} = -\frac{m}{\mu}$), then (A.1) becomes

$$1 - erf\left(\frac{\lambda-\mu}{\sigma\sqrt{2}}\right) = \frac{2\gamma m/\mu}{(b - m(\lambda/\mu))^2}. \tag{A.2}$$

Part 2: Formulation of the Reservation Price (Equation (8))Used in the Numerical Solution

An alternative form of the reservation price equation is

$$0 = -\rho\varepsilon + \int_{\varepsilon^*}^{\lambda} x_N \phi(x_N)\, dx_N + \lambda \int_{\lambda}^{\infty} \phi(x_N)\, dx_N - \frac{\gamma}{f}. \tag{A.3}$$

Substituting in the normality assumption for $\phi(x_N)$ and (11) yields a series of terms for the four expressions in (A.3). In (A.3), the first, third and fourth terms are, respectively

$$-\rho\varepsilon = -\varepsilon \int_{\varepsilon^*}^{\lambda} \varphi(x_N)\, dx_N = -(\varepsilon/2)\left[1 - erf\left(\frac{\varepsilon - \mu}{\sigma\sqrt{2}}\right)\right],$$

$$\lambda \int_{\lambda}^{\infty} \phi(x_N)\, dx_N = \frac{\lambda}{2}\left[1 - erf\left(\frac{\lambda - \mu}{\sigma\sqrt{2}}\right)\right]$$

and

$$-\frac{\gamma}{f} = -\frac{\gamma}{b - m(\lambda/\mu)}.$$

The second term is

$$\int_{\varepsilon}^{\lambda} x_N \varphi(x_N)\, dx_N = \int_{\varepsilon'}^{\lambda'} \sigma \frac{\sqrt{2}}{\sqrt{\pi}} z e^{-z^2}\, dz + \int_{\varepsilon'}^{\lambda'} \frac{\sqrt{\mu}}{\sqrt{\pi}} e^{-z^2}\, dz,$$

where $z = \frac{(x-\mu)}{\sigma\sqrt{2}}$, $\varepsilon' = \frac{(\varepsilon-\mu)}{\sigma\sqrt{2}}$ and $\lambda' = \frac{(\lambda-\mu)}{\sigma\sqrt{2}}$. Simplifying the right-hand side yields

$$\int_{\varepsilon}^{\lambda} x_N \varphi(x_N)\, dx_N = -\frac{\sigma}{\sqrt{2\pi}}\left[e^{-\frac{1}{2}\left(\frac{\lambda-\mu}{\sigma}\right)^2} - e^{-\frac{1}{2}\left(\frac{\varepsilon-\mu}{\sigma}\right)^2}\right] + \frac{\mu}{2}\left[erf\left(\frac{\lambda - \mu}{\sigma\sqrt{2}}\right) - erf\left(\frac{\varepsilon - \mu}{\sigma\sqrt{2}}\right)\right].$$

Recombining the four parts of (A.3) yields

$$0 = \frac{(\varepsilon - \mu)}{2}\left[erf\left(\frac{\varepsilon - \mu}{\sigma\sqrt{2}}\right) - \frac{(\lambda - \mu)}{2} erf\left(\frac{\lambda - \mu}{\sigma\sqrt{2}}\right)\right] + \frac{\sigma}{\sqrt{2\pi}}\left[e^{-\frac{1}{2}\left(\frac{\varepsilon-\mu}{\sigma}\right)^2} - e^{-\frac{1}{2}\left(\frac{\lambda-\mu}{\sigma}\right)^2}\right] + \frac{(\lambda - \varepsilon)}{2} - \frac{\gamma}{(b - m(\lambda/\mu))}. \tag{A.4}$$

Once λ is found from (A.2), then (A.4) can be used to solve for ε.

Table A1 ■ Selection bias corrected hedonic price estimation: Dublin, OH.

Half baths	3,254.69 [0.71]	Mother-in-law suite	−28,813.15 [2.48]**
Full baths	33,600.23 [13.98]***	Lake front	4,446.56 [0.17]
Bedrooms	−17,738.06 [7.25]***	Handicap access	−16,207.24 [1.25]
Square feet available	132.985 [25.02]***	Golf course lot	32,491.51 [3.00]***
Squared sq. ft.	−0.001 [23.62]***	Farm building	40,958.42 [0.79]
Whirlpool	16,369.06 [4.87]***	Above-ground pool	38,146.06 [0.55]
Well	73,562.60 [3.99]***	1998	−8,613.35 [0.86]
Waste treatment	−16,541.49 [1.13]	1999	245.052 [0.02]
Some wood floors	6,583.66 [1.70]*	2000	12,455.42 [1.46]
Security system	18,915.37 [5.38]***	2001	19,061.59 [1.79]*
Screen porch	1,195.83 [0.27]	2002	42,974.56 [8.26]***
Patio	802.865 [0.26]	2003	56,017.54 [10.42]***
In-ground pool	−6,533.40 [0.65]	2004	69,323.78 [12.97]***
Deck	−22,299.08 [6.62]***	2005	67,733.60 [3.64]***
Stream on lot	−14,076.78 [0.79]	Quarter 2	4,987.33 [1.21]
River front	108,199.51 [3.52]***	Quarter 3	88.979 [0.01]
Ravine lot	24,250.82 [1.32]	Quarter 4	7,168.07 [1.34]
Pond on property	16,361.13 [1.00]	Constant	−76,621.76 [3.67]***
		Inverse mills ratio	−80,520.32 [−1.85]
Observations	6,244		
Censored obs.	1,464		
Uncensored obs.	4,780		
Wald chi-sq. (69)	10,510.87		
Prob. > chi-sq.	<0.001		

Notes: The table lists the estimated coefficients, and standard errors are in brackets. This is an example of an estimation for one of the sampled localities. The coefficients are employed in the calculation of atypicality. The sample period is from 1997 to 2005. Because the factors that affect the sales price of a house are generally the same as those that affect the probability of sale, identification is achieved via the nonlinearity of the creation of the sample selection correction variable.