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

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Abstract

Many goods are marketed after first stating a list price, with the expectation that the eventual sales price will differ. In this paper we first extend search theory to include 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 tradeoff determines the optimal list price, which is set simultaneously with the seller's reservation price. Comparative statics are derived through a set 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. Other applications could include the market for fine art or autos.

1. Introduction

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 2005, 7.075 million existing homes and 1.283 million 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, the fine art market, and it occurs in some internet auctions.

We first generalize optimal stopping rules to allow sellers to set 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 at a decreasing rate as the atypicality of a property increases.

The next section of the paper reviews the theoretical literature about list price determination and it describes how we generalize the optimal stopping rule model to include list prices. We then derive the model's testable hypotheses using a numerical model, focusing on the impact on list price of a product's attributes. We also highlight the relationships between a product's characteristics and list price, expected sale price, and marketing time. Section 4 describes our housing data set for the Columbus, Ohio MSA. The empirical results are reported in section 5 of the paper and we summarize the findings in section 6.

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[1] "U.S. Housing Market Conditions 1st Quarter, 2006" Tables 6 and 7 (HUD User 2006).

2. 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 including 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

The seller of an asset has the ability to set a list price, which we assume remains constant during the search. The buyer 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]

We make two assumptions about the role of list prices in a seller's strategy. First, we assume that sellers assume that potential buyers who value a property at a level

[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 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.

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 of a good, holding constant the quality and quantity of the product, 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 and we argue that it is not rational for sellers to expect that it will occur.[6] Rather, sellers should expect that their posted list price is essentially an offer to sell at that price. The second assumption is that higher list prices convey, on average, higher quality. If a potential buyer views an "overpriced" property's characteristics either on-line 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 n^{th} offer,

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[4] This assumption, when applied to the housing market, results in the model being relatively more applicable to the U.S. 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.

V_n = revenue at the time of the n^{th} offer, given the value of the n^{th} 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]

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

and

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

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

(2) $E(R_N|N) = E(X_N|N) - \frac{\gamma}{f} N$, where X_N is the value of N^{th} offer. Expecting out the N yields:

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

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.

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

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

[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.

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

$E(X_N)$ 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.

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

In (5), there are four alternatives. The first occurs when an offer is less that 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:

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

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

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

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

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

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

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

Combining (3) and (7b) yields:

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

Rewriting (9) yields:

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

The solutions for λ^* and ε^* are found from (8) and (10). These must be solved 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:

(11) $$f(\lambda) = b - m(\lambda / \mu)$$

where μ is the mean of the buyers' distribution of offers. In (11), the "baseline" arrival rate is b, this reduced 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):

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

where erf is the "error function"

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

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

In (12) we observe that λ^* can be determined given the parameters of the model and 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 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 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 the 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 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 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 (1988) 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

[9] The latter two are expected values and thus 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-Ortalo-Magne (2004) (in-depth description of list prices in the housing market).

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 foregoing an offer from the upper tail of the buyer distribution, and information about the distribution of potential offers can be obtained from real estate agents and monitoring the level of seller interest in a property (for example, attendance at open houses).

3. Numeric Solutions

Equations (8) and (12) must be solved using numeric 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 focus is one how these values vary with the standard deviation of the distribution of offers by potential buyers. The baseline set of parameters and solution are listed in Table 1. We next vary the standard deviation of buyers' offers from 0 to 10% of the mean of the offer distribution. Also computed are the ratio of the list price to the reservation price and the ratio of the list price to the expected sales price. The latter ratio is of substantial interest because it is observable in many data sets for sold properties.

[INSERT TABLE 1]

The relationship of the solutions to the standard deviation of the distribution of buyers' offer is displayed in Figure 1. 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 nine months due to changes in the seller's strategy. The middle panel shows that the ratio of the list price to the expected sales price rises at a decreasing rate with increases in σ . Thus, owners of atypical assets; that is, ones with a relatively large variance of opinions about its worth, will set list prices relatively high, and on average have a relatively high list price compared to the expected selling price. This latter result implies these owners will agree to a relatively large discount from their list price, but still sell for a higher price than a more typical property with same mean valuation.

[INSERT FIGURE 1]

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 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 a little, and it only modestly reduces the maximal offer. This small reduction thus 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.

[INSERT TABLE 2]

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 six months. In the baseline case, the expected sales price is $204,270, while in this down market case it falls to $199,780.

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.[12] In this case, the reservation price is set in the same way as in a model where list price is excluded from the analysis.

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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 2006, Tables 7 and 25). The peak sales years were in the late 1970s and 1999-2005, and the trough years occurred in 1970-75 and 1981-1985.

[12] 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.

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 typical time period. This could be restated in this model as requiring 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.

4. Data

We test one 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 the larger is the variance of the distribution of buyers' offers. To implement this test, 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. Part 3 of the appendix describes the creation of this variable in more detail.

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 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 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 contains a listing's initial list price, house characteristics, and the sales price (if sold) for all houses listed in the MLS.[13] The metropolitan area includes eight suburban jurisdictions that 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. Table 3 presents a

[13] 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.

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 to be relatively uniform, while it is larger in the older established suburbs of Bexley and Upper Arlington.

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 can test 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 (Panel B) 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 ratio increases monotonically as the atypicality measure rises from decile to decile.

[INSERT TABLE 3]

5. 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 4a we limit the sample to homes that sold and use the actual sales price as the value of the expected sales price. The left panel of results excludes time dummy variables, while the right panel includes them. Throughout the results, inclusion of the time dummies has little effect on the signs or significance of the atypicality variable.

The numerical solutions and sensitivity tests suggested that the greater a property's atypicality, the higher the list price to expected sales price ratio. Panel B of Figure 1 suggests that the relationship should be nonlinear, the price ratio rising at a decreasing rate as the variance rises. Thus we test for both linear and nonlinear effects.

In Panel A of Table 4a, the results of a linear specification are reported. In every suburb, the atypicality variable is positive and significant, as expected. In Panel B the linear specification is retained, but the atypicality variable is measured differently: the Heckman correction is ignored when developing the implicit house characteristic prices needed to calculate atypicality. Thus Panel B is the most simplistic empirical formulation. Again, atypicality is significant in every suburb. In Table 4b, the specification is changed to allow a nonlinear impact of atypicality, with the expectation being that the positive effect will diminish with increased size. In this specification, the results are generally supportive as the square of atypicality is negative and significant in the aggregate estimation, but is negative and significant in only two of eight suburbs (Panel A, with time dummy variables).

Table 5 follows a similar format, except now the sample is expanded to contain all listed houses, this 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. In Table 5a, the linear specification again finds that the measure of atypicality is significant and positive in every case, supporting the claim that atypical houses have a higher list to expected sales price ratio. The most preferred specification is in Table 5b, Panel A, right side columns (which contain the time period dummy variables). Here, the result for the aggregation of all sales is the expected positive, but attenuating, effect of atypicality on the price ratio. Negative and significant effects for atypicality-squared are found for five of eight suburbs. In two (Dublin and Hilliard), the results suggest that the list to expected sales price ratio rises at an increasing rate with atypicality.

[INSERT TABLES 4 and 5]

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-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 5b, Panel A), this increase in atypicality raises the price ratio by 0.030; that is, list price is raised 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 1.5% to 9.7% among the suburbs, but it is likely that much of this inter-suburb variation is due to the smaller sample sizes.

6. Conclusions

List prices differ from sales prices in many markets. This paper extends 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. Other applications include the market for new and used cars and the market for fine art. 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 strong confirmation that increased atypicality raises the ratio of list to sales price, but at a decreasing rate.

A number of other interesting observations are derived from the numerical analysis of list price determination. The owners of highly atypical properties set list price relatively high, but 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 being 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 booming periods of sales, one would expect, counter intuitively, that sellers' discounts from list prices will be relatively high. The discounts will be smaller during down markets due to the much lower list price adopted by the seller. 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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Table 1: Parameter and Solution Values for the Baseline Case

Parameter	Definition	Baseline Value
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

Table 2: Variation in Baseline Solution as Parameter Values Change (Baseline Cases are in Bold)

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
	1000	**209,770**	**201,640**	**204,270**	**1.027**	**2.638**
	1500	209,190	200,500	203,490	1.028	1.989
	2000	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

Table 3: Means and Standard Deviations for Eight Suburban Samples

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. The sample is from 1997-2005.

Panel A: Total Sample Summary Statistics

	Total Obs	Sold Obs	% Sold	List Price Mean	List Price Std Dev
Aggregate	47590	34846	73.2%	242.5	186.9
Bexley	2731	1997	73.1%	286.4	238.4
Dublin	8248	5855	70.9%	320.5	217.4
Gahanna	6085	4639	76.2%	198.7	141.2
Hilliard	5637	4055	71.9%	200.8	110.2
Pickerington	8563	5533	64.6%	200.9	160.7
Upper Arlington	6814	5330	78.2%	307.4	240.3
Westerville	6824	5277	77.3%	201.1	139.5
Worthington	2688	2160	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	34846	214.7	222.7	66.83	124.9	134.5	82.5
Bexley	1997	243.8	258.5	118.1	167.7	185.1	101.8
Dublin	8248	283.9	293.3	95.5	137.9	144.6	88.4
Gahanna	4639	179.6	184.7	52.5	94.7	98.8	51.4
Hilliard	4055	182.9	188.4	23.2	94.3	99.4	21.8
Pickerington	5533	176.6	181.6	33.2	75.7	79.9	60.2
Upper Arlington	5330	262.6	277	121.2	168.5	187.8	114.2
Westerville	5277	181.9	187	51.8	78.2	81.7	53.1
Worthington	2160	194.8	202.4	42.9	89.4	96.8	65.1

Note: All numbers in reported in thousands.

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

Decile	Average Atypicality	List Price/Sales 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 4a: Linear Estimation of the Relationship of the Ratio of List Price to Actual Sales Price with Atypicality

Panel A of the table reports the OLS estimates obtained from a regression of the ratio of list price to expected sales price on the a-typicality 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 for the years 1997-2005. Panel B employs the same specification as Panel A, but the a-typicality variable is calculated without Heckman-corrected coefficients on each of the atypicality inputs. Please refer to the appendix for a thorough explanation of the construction of the atypicality variable. The sample is from 1997-2005.

Panel A	Constant	Atypicality	Adj R^2	Constant	Atypicality	Adj R^2
		Without time dummy variables			*With time dummy variables*	
Bexley	1.04	9.67E-08	0.03	1.031	9.24E-08	0.058
	[518.73]***	[7.98]***		[211.34]***	[7.70]***	
Dublin	1.03	5.64E-08	0.022	1.025	5.50E-08	0.039
	[1559.30]***	[11.48]***		[548.50]***	[11.12]***	
Gahanna	1.02	6.42E-08	0.010	1.026	5.61E-08	0.036
	[1374.03]***	[7.02]***		[508.40]***	[6.14]***	
Hilliard	1.02	1.05E-07	0.025	1.02	9.97E-08	0.057
	[1081.96]***	[9.43]***		[364.97]***	[9.09]***	
Pickerington	1.03	3.14E-08	0.005	1.024	2.62E-08	0.036
	[1812.55]***	[5.49]***		[480.97]***	[4.63]***	
Upper Arlington	1.04	7.75E-08	0.024	1.04	7.41E-08	0.068
	[961.18]***	[11.59]***		[366.84]***	[11.31]***	
Westerville	1.03	5.52E-08	0.007	1.024	5.12E-08	0.039
	[1490.05]***	[6.25]***		[521.67]***	[5.86]***	
Worthington	1.03	5.06E-08	0.009	1.034	4.94E-08	0.037
	[857.49]***	[4.61]***		[252.47]***	[4.55]***	
Aggregate	1.03	8.27E-08	0.030	1.026	7.96E-08	0.055
	[3431.65]***	[32.26]***		[1136.54]***	[31.39]***	

Panel B	Constant	Atypicality	Adj R^2	Constant	Atypicality	Adj R^2
		Without time dummy variables			*With time dummy variables*	
Bexley	1.04	1.00E-07	0.03	1.029	9.87E-08	0.059
	[524.05]***	[7.86]***		[207.46]***	[7.80]***	
Dublin	1.03	5.98E-08	0.022	1.025	5.81E-08	0.039
	[1520.21]***	[11.52]***		[546.47]***	[11.13]***	
Gahanna	1.02	7.10E-08	0.010	1.026	6.22E-08	0.036
	[1369.29]***	[6.97]***		[507.98]***	[6.12]***	
Hilliard	1.02	3.01E-07	0.034	1.02	2.78E-07	0.058
	[1283.88]***	[12.07]***		[468.02]***	[11.19]***	
Pickerington	1.03	4.88E-08	0.006	1.024	4.19E-08	0.036
	[1799.66]***	[5.90]***		[532.83]***	[5.12]***	
Upper Arlington	1.04	7.58E-08	0.025	1.039	7.24E-08	0.068
	[958.76]***	[11.67]***		[366.19]***	[11.36]***	
Westerville	1.02	6.38E-08	0.008	1.023	5.91E-08	0.040
	[1423.06]***	[6.57]***		[515.54]***	[6.15]***	
Worthington	1.03	7.42E-08	0.01	1.033	7.29E-08	0.037
	[838.54]***	[4.70]***		[275.22]***	[4.66]***	
Aggregate	1.03	9.48E-08	0.033	1.025	9.21E-08	0.059
	[3544.14]***	[34.77]***		[1188.53]***	[34.10]***	

Table 4b: Nonlinear Estimation of the Relationship of the Ratio of List Price to Actual Sales Price with Atypicality

Panel A of the table reports the OLS estimates obtained from a regression of the ratio of list price to expected sales price on the a-typicality 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 for the years 1997-2005. Panel B employs the same specification as Panel A, but the a-typicality variable is calculated without Heckman-corrected coefficients on each of the atypicality inputs. Please refer to the appendix for a thorough 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 1997-2005.

Panel A	Constant	Atypicality	$Atypicality^2$	Adj R^2	Constant	Atypicality	$Atypicality^2$	Adj R^2
		Without time dummy variables				*With time dummy variables*		
Bexley	1.041	7.57E-08	3.41E-14	0.03	1.033	6.86E-08	3.86E-14	0.058
	[399.95]***	[3.20]***	[1.03]		[197.20]***	[2.92]***	[1.18]	
Dublin	1.029	1.75E-08	8.62E-14	0.026	1.027	1.05E-08	9.84E-14	0.044
	[1317.77]***	[1.95]*	[5.21]***		[540.51]***	[1.17]	[5.95]***	
Gahanna	1.024	6.57E-08	-6.33E-15	0.010	1.026	4.43E-08	4.93E-14	0.036
	[1171.26]***	[3.71]***	[0.10]		[505.40]***	[2.50]**	[0.77]	
Hilliard	1.021	9.44E-08	4.64E-14	0.025	1.021	8.70E-08	5.58E-14	0.057
	[892.15]***	[4.35]***	[0.57]		[354.02]***	[4.07]***	[0.69]	
Pickerington	1.022	9.84E-08	-1.57E-14	0.013	1.023	7.95E-08	-1.24E-14	0.040
	[1442.13]***	[8.39]***	[6.53]***		[476.99]***	[6.77]***	[5.17]***	
Upper Arlington	1.037	8.16E-08	-2.04E-15	0.024	1.04	7.35E-08	2.88E-16	0.068
	[775.50]***	[8.08]***	[0.54]		[350.96]***	[7.40]***	[0.08]	
Westerville	1.024	7.48E-08	-2.68E-14	0.008	1.023	6.79E-08	-2.28E-14	0.040
	[1261.50]***	[5.61]***	[1.95]*		[503.01]***	[5.14]***	[1.69]*	
Worthington	1.032	7.31E-08	-1.00E-14	0.01	1.033	6.33E-08	-6.18E-15	0.037
	[656.87]***	[3.16]***	[1.10]		[248.68]***	[2.75]***	[0.68]	
Aggregate	1.026	1.34E-07	-2.07E-14	0.044	1.027	1.29E-07	-1.98E-14	0.072
	[2039.47]***	[27.69]***	[12.88]***		[726.97]***	[27.07]***	[12.49]***	

Panel B	Constant	Atypicality	$Atypicality^2$	Adj R^2	Constant	Atypicality	$Atypicality^2$	Adj R^2
		Without time dummy variables				*With time dummy variables*		
Bexley	1.044	4.18E-08	1.17E-13	0.032	1.034	3.97E-08	1.18E-13	0.062
	[407.82]***	[1.57]	[2.49]**		[195.37]***	[1.50]	[2.55]**	
Dublin	1.029	1.78E-08	9.71E-14	0.026	1.027	9.87E-09	1.11E-13	0.044
	[1264.15]***	[1.85]*	[5.18]***		[536.68]***	[1.03]	[5.95]***	
Gahanna	1.024	6.98E-08	5.77E-15	0.010	1.026	4.68E-08	7.16E-14	0.036
	[1168.27]***	[3.56]***	[0.07]		[504.62]***	[2.39]**	[0.92]	
Hilliard	1.021	2.82E-07	1.37E-13	0.034	1.021	2.44E-07	2.45E-13	0.059
	[1120.92]***	[7.50]***	[0.66]		[458.42]***	[6.51]***	[1.19]	
Pickerington	1.023	1.27E-07	-3.01E-14	0.013	1.021	1.07E-07	-2.49E-14	0.040
	[1466.54]***	[8.32]***	[6.09]***		[511.10]***	[7.02]***	[5.06]***	
Upper Arlington	1.037	7.84E-08	-1.30E-15	0.025	1.04	7.05E-08	9.66E-16	0.068
	[779.17]***	[8.07]***	[0.36]		[350.57]***	[7.37]***	[0.27]	
Westerville	1.024	7.05E-08	-1.49E-14	0.008	1.023	6.23E-08	-7.09E-15	0.040
	[1237.16]***	[4.98]***	[0.65]		[501.70]***	[4.44]***	[0.31]	
Worthington	1.032	9.77E-08	-1.65E-14	0.01	1.032	8.69E-08	-9.84E-15	0.037
	[645.92]***	[3.18]***	[0.89]		[261.46]***	[2.84]***	[0.53]	
Aggregate	1.044	4.18E-08	1.17E-13	0.032	1.034	3.97E-08	1.18E-13	0.062
	[407.82]***	[1.57]	[2.49]**		[195.37]***	[1.50]	[2.55]**	

Table 5a: Linear Estimation of the Relationship of the Ratio of List Price to Expected Sales Price with Atypicality

This table reports the OLS 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 is computed using a Heckman corrected equation. Panel B reports results without the Heckman correction in either of the expected sales price or atypicality measures. The sample is from 1997-2005.

Panel A	Constant	Atypicality	Adj R^2	Constant	Atypicality	Adj R^2
		Without time dummy variables			*With time dummy variables*	
Bexley	0.807	4.68E-07	0.033	0.709	4.66E-07	0.137
	[81.26]***	[8.88]***		[24.60]***	[9.32]***	
Dublin	0.924	2.96E-07	0.015	0.876	2.94E-07	0.023
	[229.84]***	[10.48]***		[70.09]***	[10.37]***	
Gahanna	0.853	7.83E-07	0.016	0.787	7.48E-07	0.05
	[120.90]***	[9.17]***		[38.50]***	[8.87]***	
Hilliard	0.767	4.51E-07	0.024	0.581	3.97E-07	0.398
	[208.87]***	[10.83]***		[67.92]***	[12.12]***	
Pickerington	1.117	2.79E-07	0.006	1.194	2.68E-07	0.036
	[256.39]***	[6.43]***		[63.31]***	[6.26]***	
Upper Arlington	1.064	3.33E-07	0.012	1.185	3.42E-07	0.020
	[156.99]***	[8.55]***		[59.72]***	[8.80]***	
Westerville	1.034	4.06E-07	0.007	1.065	3.95E-07	0.011
	[250.56]***	[6.37]***		[100.58]***	[6.19]***	
Worthington	1.031	5.30E-07	0.019	1.073	5.28E-07	0.02
	[160.91]***	[6.67]***		[59.81]***	[6.60]***	
Aggregate	0.977	2.76E-07	0.007	0.974	2.71E-07	0.011
	[493.57]***	[16.79]***		[147.17]***	[16.52]***	
Panel B	Constant	Atypicality	Adj R^2	Constant	Atypicality	Atypi Adj R^2
		Without time dummy variables			*With time dummy variables*	
Bexley	1.017	7.36E-07	0.034	1.155	7.58E-07	0.049
	[72.88]***	[9.06]***		[27.32]***	[9.37]***	
Dublin	1.026	3.58E-07	0.016	1.065	3.61E-07	0.017
	[224.22]***	[10.80]***		[76.22]***	[10.80]***	
Gahanna	1.002	1.07E-06	0.020	1.059	1.07E-06	0.022
	[128.30]***	[10.19]***		[45.98]***	[10.17]***	
Hilliard	1.031	5.76E-07	0.005	1.061	5.77E-07	0.011
	[284.13]***	[5.09]***		[101.34]***	[5.07]***	
Pickerington	1.052	2.46E-07	0.003	1.084	2.35E-07	0.006
	[271.32]***	[4.39]***		[64.55]***	[4.18]***	
Upper Arlington	1.045	2.75E-07	0.003	1.09	2.84E-07	0.003
	[92.94]***	[4.41]***		[33.08]***	[4.53]***	
Westerville	1.022	4.14E-07	0.007	1.042	4.04E-07	0.009
	[251.19]***	[6.66]***		[99.74]***	[6.48]***	
Worthington	1.035	2.79E-07	0.002	1.062	2.70E-07	0.002
	[160.12]***	[2.49]**		[60.92]***	[2.40]**	
Aggregate	1.035	3.85E-07	0.009	1.074	3.85E-07	0.011
	[476.59]***	[19.63]***		[143.82]***	[19.64]***	

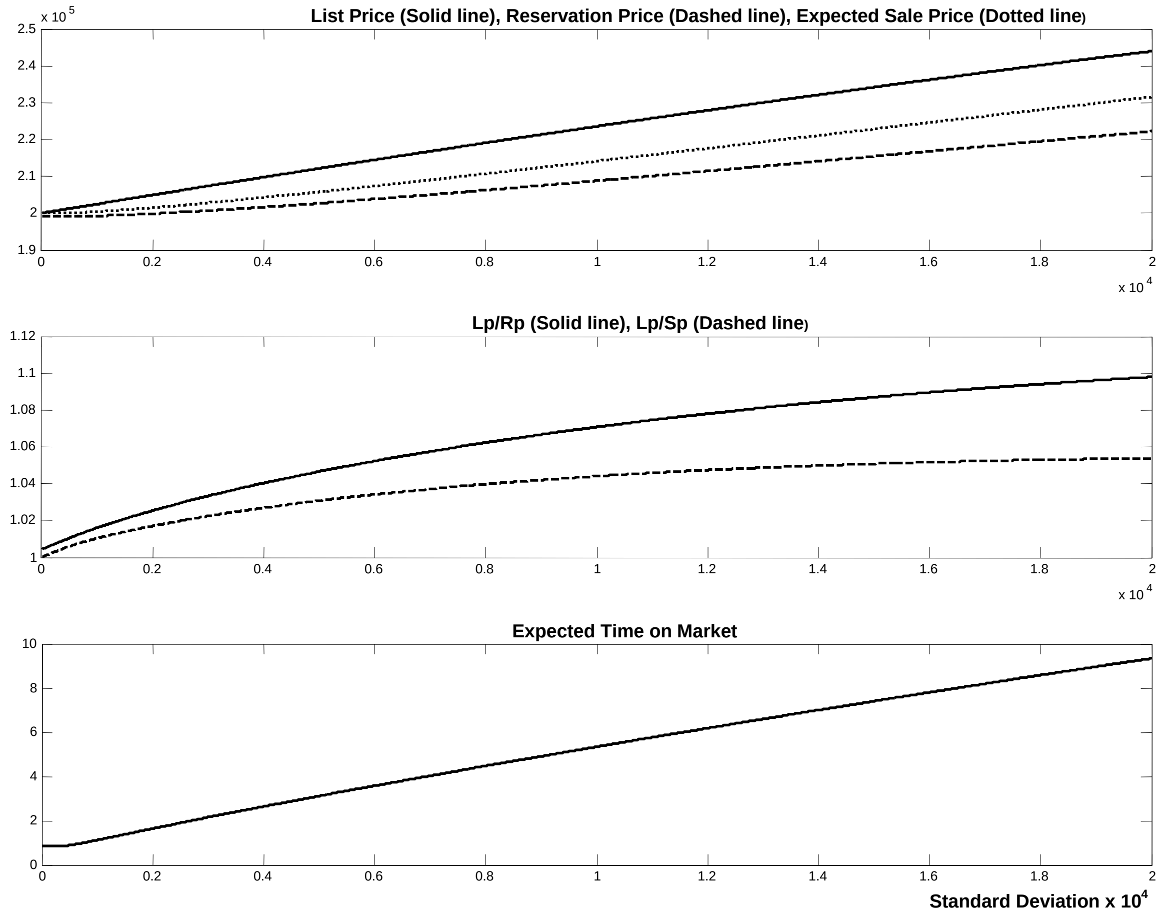
Table 5b: Nonlinear Estimation of the Relationship of the Ratio of List Price to Expected Sales Price with Atypicality

This table reports the OLS 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 is 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 1997-2005.

Panel A	Constant	Atypicality	Atypicality^2	Adj R^2	Constant	Atypicality	Atypicality^2	Adj R^2
		Without time dummy variables				*With time dummy variables*		
Bexley	0.78	7.43E-07	-3.84E-13	0.036	0.676	8.11E-07	-4.81E-13	0.141
	[55.51]***	[6.39]***	[2.65]***		[22.30]***	[7.36]***	[3.51]***	
Dublin	0.93	2.15E-07	1.24E-13	0.016	0.881	2.12E-07	1.25E-13	0.024
	[197.08]***	[4.89]***	[2.41]**		[69.36]***	[4.82]***	[2.43]**	
Gahanna	0.844	1.02E-06	-9.47E-13	0.017	0.781	9.30E-07	-7.13E-13	0.05
	[98.26]***	[6.55]***	[1.84]*		[37.46]***	[6.02]***	[1.41]	
Hilliard	0.774	2.53E-07	8.03E-13	0.025	0.589	2.03E-07	7.87E-13	0.4
	[172.66]***	[3.08]***	[2.81]***		[66.93]***	[3.14]***	[3.50]***	
Pickerington	1.059	1.46E-06	-2.59E-13	0.042	1.145	1.47E-06	-2.62E-13	0.073
	[191.64]***	[17.62]***	[16.62]***		[61.20]***	[17.92]***	[17.06]***	
Upper Arlington	1.026	6.90E-07	-2.83E-13	0.020	1.144	7.09E-07	-2.89E-13	0.029
	[119.82]***	[10.97]***	[7.21]***		[55.86]***	[11.26]***	[7.38]***	
Westerville	1.025	7.33E-07	-2.03E-12	0.008	1.056	7.06E-07	-1.93E-12	0.012
	[201.51]***	[5.65]***	[2.90]***		[95.98]***	[5.44]***	[2.76]***	
Worthington	1.01	1.03E-06	-1.39E-12	0.03	1.051	1.03E-06	-1.40E-12	0.032
	[135.01]***	[8.42]***	[5.35]***		[57.59]***	[8.42]***	[5.40]***	
Aggregate	0.983	4.59E-07	-1.06E-13	0.012	0.995	4.57E-07	-1.05E-13	0.015
	[315.88]***	[16.69]***	[10.81]***		[100.59]***	[16.64]***	[10.80]***	

Panel B	Constant	Atypicality	Atypicality^2	Adj R^2	Constant	Atypicality	Atypicality^2	Adj R^2
		Without time dummy variables				*With time dummy variables*		
Bexley	0.922	1.88E-06	-1.95E-12	0.053	1.056	1.92E-06	-1.99E-12	0.068
	[46.60]***	[9.94]***	[6.68]***		[23.87]***	[10.25]***	[6.87]***	
Dublin	1.027	3.43E-07	2.31E-14	0.016	1.066	3.50E-07	1.72E-14	0.017
	[189.52]***	[6.62]***	[0.36]		[74.82]***	[6.70]***	[0.27]	
Gahanna	0.982	1.68E-06	-2.66E-12	0.023	1.042	1.68E-06	-2.65E-12	0.025
	[103.68]***	[8.82]***	[3.84]***		[44.36]***	[8.79]***	[3.82]***	
Hilliard	1.035	2.62E-07	3.21E-12	0.005	1.065	2.83E-07	2.98E-12	0.011
	[220.92]***	[1.12]	[1.55]		[98.07]***	[1.20]	[1.43]	
Pickerington	1.011	1.42E-06	-4.03E-13	0.027	1.051	1.41E-06	-4.03E-13	0.030
	[206.66]***	[13.77]***	[13.51]***		[62.65]***	[13.65]***	[13.49]***	
Upper Arlington	1.013	5.68E-07	-2.31E-13	0.005	1.056	5.84E-07	-2.36E-13	0.005
	[71.29]***	[5.62]***	[3.67]***		[30.94]***	[5.75]***	[3.75]***	
Westerville	1.015	6.91E-07	-1.72E-12	0.008	1.035	6.67E-07	-1.63E-12	0.010
	[202.13]***	[5.38]***	[2.46]**		[95.25]***	[5.19]***	[2.34]**	
Worthington	1.013	9.78E-07	-2.82E-12	0.014	1.04	9.79E-07	-2.85E-12	0.013
	[132.23]***	[5.62]***	[5.23]***		[58.40]***	[5.60]***	[5.28]***	
Aggregate	0.922	1.88E-06	-1.95E-12	0.053	1.056	1.92E-06	-1.99E-12	0.068
	[46.60]***	[9.94]***	[6.68]***		[23.87]***	[10.25]***	[6.87]***	

Figure 1: Variations in Baseline Solutions Due to Changes in the Standard Deviation of the Distribution of Buyers' Offers



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:

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

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:

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

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

An alternative form of the reservation price equation is:

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

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:

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

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

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

The second term is:

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

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:

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

Recombining the four parts of (A-3) yields:

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

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

Part 3: Creation of the Atypicality Measure: An Example of a Hedonic House Price Estimation

The atypicality measure (A) for the i-th property in the j-th jurisdiction is defined as:

(A-5) $$A_{ij} = \sum_k p_k \mid h_{kij} - \bar{h}_{kj} \mid$$

where the h_{kij} are the characteristics of a property, $\bar{h}_{jk}$ is the mean value of the k-th characteristic in the j-th 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. Table A-1 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 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.

Table A-1

Table 4 presents the results of a sample Heckman two-step model that produces estimates of the coefficients employed in the calculation of atypicality. This sample estimation uses data from Dublin, Ohio from 1997-2005.

	Sold Price		
Half Baths	3,254.69	Mother-in-Law Suite	-28,813.15
	[0.71]		[2.48]**
Full Baths	33,600.23	Lake Front	4,446.56
	[13.98]***		[0.17]
Bedrooms	-17,738.06	Handicap Access	-16,207.24
	[7.25]***		[1.25]
Square Feet Available	132.985	GolfCourse Lot	32,491.51
	[25.02]***		[3.00]***
Squared Sq Ft.	-0.001	Farm Building	40,958.42
	[23.62]***		[0.79]
Whirl Pool	16,369.06	Above Ground Pool	38,146.06
	[4.87]***		[0.55]
Well	73,562.60	1998	-8,613.35
	[3.99]***		[0.86]
Waste Treatment System	-16,541.49	1999	245.052
	[1.13]		[0.02]
Some Wood Floors	6,583.66	2000	12,455.42
	[1.70]*		[1.46]
Secuirty System	18,915.37	2001	19,061.59
	[5.38]***		[1.79]*
Screen Porch	1,195.83	2002	42,974.56
	[0.27]		[8.26]***
Patio	802.865	2003	56,017.54
	[0.26]		[10.42]***
In Ground Pool	-6,533.40	2004	69,323.78
	[0.65]		[12.97]***
Deck	-22,299.08	2005	67,733.60
	[6.62]***		[3.64]***
Stream on Lot	-14,076.78	Quarter 2	4,987.33
	[0.79]		[1.21]
River Front	108,199.51	Quarter 3	88.979
	[3.52]***		[0.01]
Ravine Lot	24,250.82	Quarter 4	7,168.07
	[1.32]		[1.34]
Pond on Property	16,361.13	Constant	-76,621.76
	[1.00]		[3.67]***
		Inverse Mills Ratio	-80520.32
			[-1.85]
Observations	6244		
Censored Obs	1464		
Uncensored Obs	4780		
Wald chi-sq(69)	10510.87		
Prob > chi-sq	<.001		