The Trade-off Between the Selling Price of Residential Properties and Time-on-the-Market: The Impact of Price Setting

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Abstract

When a house is placed on the market, the seller must choose the initial offer price. Setting the price too high or too low affects the marketability of the property. While there is near universal agreement that a house seller faces a trade off between selling at a higher price and selling in less time, there is less agreement about how to measure this trade off. This paper offers a framework for analysis and shows that a higher list price increases expected time-on-the-market. Since house buyers must solve a type of signal extraction problem, the effect of a higher list price is magnified for houses with a low predicted variance of the list price. This paper also shows that the list price of houses which are withdrawn before sale has a higher mean and variance, and that the possibility of withdrawal censors information about the time-on-the-market.

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1. Introduction

Research has shown that the seller of a residential property generally faces a trade-off between the time it takes to sell a house and the price eventually received. Furthermore, the initial pricing of the property by the seller plays a critical role in the marketing of the property. By setting too high an initial price, a seller may discourage participation by potential buyers and risk having the property on the market for an overly long time period. Conversely, if the initial price is too low, the seller may effect a quick sale at the cost of selling the property for less than could have been received with better market exposure.

Beginning with the premise that the time-on-the-market (TOM) depends on the listing price because the listing price may influence the rate at which buyers inspect a house, we propose a simple model of the impact of the seller's pricing decision. We assume that the listing price acts as a signal to potential buyers indicating which houses are in his price range. From the seller's perspective, if the listing price is substantially higher than the expected list price then the house is more likely to be excluded from a buyer's "price range" of houses. If the house is inspected, a buyer is less likely to buy the house after evaluating its price and amenities relative to those of other houses that the buyer has inspected. One of the critical elements of this model is the Degree of OverPricing, ***DOP***, measured as the percentage difference between the actual listing price and the expected listing price, given the observable characteristics of the house. Houses with a smaller deviation from their expected listing price should sell faster. Also, any effect of an increase in ***DOP*** is magnified for houses in a market niche characterized by limited list price variance.

We use a large data set from a multiple listing service from which we can identify both properties that were eventually sold and properties which were withdrawn from the market. By including "withdrawn" houses in the time-on-the-market model, we control for a downward bias in marketing times common to these types of models. The empirical results show that increases in the ***DOP*** increase the expected time-on-the-market at an increasing rate. Generally, the time-on-the-market varies significantly with few property characteristics, but more so with differences in spatial location and market conditions. We also show that the listing price and the selling price functions are not identical, suggesting they have separate roles in the housing transaction process, and that the discount ratio of the sale price to listing price has little relationship with ***DOP***.

2. Background

Economic search theory postulates that a seller who spends more time and effort in locating a buyer will find a buyer who is willing to pay a higher price for the house (see Wheaton, 1990; Yavas, 1992; for example). One can also argue that a buyer who searches more intensely has a higher probability of finding a low priced house for a specified quality (see Anglin, 1997, for example). Also, houses that remain on the market for an overly long time period often suffer from a stigma, because current buyers assume that previous buyers must have discovered a non-trivial problem associated with the house. Taylor (1999) studies this issue formally. To assess the role of the selection of the listing price in the marketing of the property, both the buyer's and seller's perspectives must be considered.

In general, the sequence of events prior to a sale is well understood. Most sellers contract with a broker who helps to choose a listing price. This price is observed by prospective buyers who use this information to choose the smaller sample of houses that they will inspect. Each buyer must infer whether spending time now to inspect a house will generate sufficient benefits in the search process. The listing price chosen by the seller is a critical factor in the selection process of the buyer. The buyer determines the price range in which he or she wants to purchase and using minimal information, the chief component of which is the listing price, chooses the set of houses to inspect more carefully. Eventually, one or more of the possible buyers, who may have entered the market at any time, makes a bid.

This argument offers no direct connection between the selling price and TOM. Any linkage between a selling price and TOM may be further obscured by the fact that both are randomly determined by the matching and bargaining processes occurring in the market. Thus, it is preferable to describe market forces as creating a locus, such as the one shown in Figure 1, which defines a "budget constraint" on the set of feasible outcomes for expected selling price and expected TOM. An individual seller makes his choice of listing price given this trade-off and his specific risk tolerance.

Insert Figure 1

This simple representation has been extended. Arnold (1999) uses a search-and-bargaining model in a theoretical treatment of the optimal listing price. In his model, the listing price attracts buyers who then inspect the asset to determine its true valuation. The buyer can then make an offer, or go to alternative opportunities. But a lower list price is not necessarily related to a shorter TOM because the types of sellers who choose a lower list price may also set a higher reservation price and use a tougher bargaining strategy. Yavas and Yang (1995) consider the impact that the seller's listing price has on seller motivation and offer empirical evidence that higher asking prices lead to longer marketing times. These studies firmly establish the role of the listing price in attraction of potential buyers to a property and the degree of effort that a real estate broker will contribute to the marketing of the property.

In terms of our Figure 1, Yavas and Yang propose that the locus should include the effects of the effort chosen by brokers. Given the complexity of this strategic interaction, a change in the list price may have an ambiguous effect on TOM (p. 356) and, therefore, the locus may slope downward for an interval. Even so, rational choice by a seller implies that only the upward sloping portions are relevant. Arnold's model proposes that a seller has two decision variables: the listing price and the reservation price. In this case, Figure 1 would show the relevant trade off for a given reservation price while an increase in the reservation price shifts the locus. At the optimum, only the outer envelope matters and it will necessarily be upward sloping (his Lemma 4).

An understanding of the role of asset atypicality is crucial to a study of housing market dynamics. Atypical houses are more difficult to market and thus function in a thinner market than "typical" houses. Haurin (1988) introduced the importance of asset atypicality, measuring the difference between a given house and an appropriately defined typical house in the market, as the driving force in explaining the variation in the marketing times of housing. In terms of Figure 1, atypicality shifts the locus to the right. Using a parametric hazard model, he found that atypicality increases time-on-the-market.

Closely related to asset atypicality is housing liquidity. Generally, houses that are more homogenous are expected to have greater liquidity. Kluger and Miller (1990) broached this topic by using a hazard model to study relative liquidity and defined a measure which estimates the differences in marketing time between houses with differing characteristics. Housing characteristics, except age, were mostly insignificant in explaining TOM. Forgey, Rutherford and Springer (1996) extended this line of research showing that time-on-the-market is explained by the age and size of the house as well as various market-related variables. They also showed that sellers of houses that are expected to sell faster than the average house benefit from the increased liquidity. In his theoretical analysis of liquidity, Krainer (2000) showed that both the sale price and the probability of sale are positively correlated with the flow of buyers: the price under bad market conditions does not fully adjust because sellers value the option of waiting to sell in the future when market conditions may improve. His analysis can be extended to show that the price level in each state depends on the persistence of market conditions.

Another critical component in a study of housing market dynamics is the role of seller motivation. Yavas and Yang (1995) consider the role of seller motivation while Arnold (1999) considers the role of the seller's discount rate and the asking price, pointing out that the asking price may serve as a signal of a seller's patience. Springer (1996) looked at the impacts of seller motivation on TOM and selling prices using separate equations. Various market and seller characteristics, including an overpricing measure, were significant in explaining TOM. Overpricing, measured as the ratio of the asking price to the expected selling price, extended marketing times and indicates lower motivation (greater patience) on the part of the seller. Glower, Hendershott and Haurin (1998), using a hazard model, also looked at the impact of seller motivations on time-on-the-market and found that sellers with either new jobs or specified moving dates were the largest influences on marketing time. In some ways, our work extends the analysis of the variable that they called *Percent Listing Error I.*

Finally, Knight (2000) looks at the impact of changes to the listing price.[1] Using two-

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[1] Knight (2000) reports that 37.5 percent of houses recorded a price change, which is less than 46 percent reported in the smaller data set of Anglin (1994). On average, the list price fell by about 7.5 percentage points, if it changed, and such houses took longer to sell in total but sold in less time after the change than a house which never changed its price. Ortola-Magne and Merlo (2000) report that about one-quarter of sellers changed their listing price before sale. They also note that changes in list price can be large: in their words, the change in list price is

stage least squares and focussing on the effect of changes in the "mark-up" (i.e. list price/sale price- 1), his results show that the impact of listing a house "too high" and then revising the listing price. Specifically, homes whose listing prices were revised took longer to sell and sold for less than homes that were initially priced "correctly." He further shows that conclusions drawn from the data are affected by whether the initial or final list price is used, although the direction of this effect appears to depend on how duration is measured.

3. Theoretical Model

Figure 1 represents the problem and, together with the seller's motivation embodied in their objective function, one can solve for the optimal list price for a particular seller. For a given market segment, defined by X, changes in listing price are easily identified and predictions can be tested. At the optimum, if an increase in p^L increases the expected selling price then the cost of selling, i.e. E(TOM) must also increase. Thus it is imprecise to talk about the "optimal time on market" or the "optimal sale price", as though either could be chosen directly, since each of these concepts ignores half of the trade-off that makes a particular listing price optimal.

But changes in X may shift the locus and change the optimal listing price. This shift occurs because houses with differing X attract different types of buyers. There is a second reason to expect TOM to depend on X if the trade off shown in Figure 1 exists. To illustrate, consider two sellers with the same taste but different houses where each buyer of the first house is willing to pay $1000 more than they are willing to pay for the second house: the price-time locus of the seller of the more valuable house is shifted in a parallel fashion by $1000 relative to the other house. Assuming that both a higher price and a shorter TOM are "normal goods", the first seller would take advantage of his/her position by selling at a higher price, but the increase would be less than $1000. The seller also benefits by selling optimally in less time. Thus both price and TOM should depend on X.[2]

"greater than the average sale price discount relative to the initial listing price". Because our data set does not reveal the timing of changes in the list price, and like most previous authors, we focus on other issues. Unobserved changes in the list price may affect the estimate of N in Table 3 since it captures duration dependent effects.

[2] We offer no hypothesis concerning the effects of changing market conditions because the analysis is too complicated for this paper. To illustrate the nature of the difficulty, consider the benchmark model used in most analyses of a housing market (Rosen, 1974). In this model, the list price (as well as TOM) is irrelevant and, since it is an equilibrium model, market conditions cannot vary in any meaningful sense. In our model, a change in market conditions may shift the locus in a parallel fashion or may rotate the locus. Deriving general predictions about the balance between these "income" and "substitution" effects is beyond the scope of this paper.

Simple consideration of the problem facing all potential buyers shows that the list price is a signal which combines two pieces of information. On one hand, the information provided by brokers concerning X enables buyers to compare houses within the same segment but buyers have an incomplete prior description of a house and an inspection may reveal valuable characteristics that would justify paying a higher price. Thus, a house may be listed higher than its apparent peer group because of features only revealed through inspection. On the other hand, a high listing price may indicate an attempt to exert bargaining power that makes the potential buyer worse off. That is, a house may be priced higher than its apparent peer group because the seller is willing to wait for his or her price. Although our data are insufficient to identify either of these motivations directly, this signal extraction problem suggests an additional hypothesis. Under reasonable conditions,[3] the types of houses with a higher variance of list prices have greater "noise" and a given change in ***DOP*** can be expected to have less effect on the behavior of a group of potential buyers.

This mechanical treatment of the process is simpler than that offered by some other models (e.g. game theoretic models) but may have an advantage when comparing housing markets in different countries. For example, in Scotland and Australia, the list price is understood to be a lower bound on the selling price rather than an upper bound as is traditional in North America.[4] A second advantage arises because some models assume that the sale price cannot exceed the list price.[5]

Methodology

The first step in the analysis is to estimate the typical list price for a house described by X. The residual of this model is used to estimate the degree of overpricng, ***DOP***, the percentage deviation from a "typical" listing price for a house in that segment, calculated as $\log(p^L)$-$E(\log(p^L); X)$. ***DOP***, is expected to affect the eventual selling price, p^S, and the time-on-the-market, TOM. The listing price model is:

$$\log(p^L) = X \text{ "} \qquad (1)$$

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[3] Suppose that the list price chosen by the seller is represented by a+ b where a represents the value of the omitted variables and b represents the influence of bargaining power. The utility of a buyer might be summarized by a- b. If a and b are independently and Normally distributed, where the variance of a is F^2 and the variance of b is s^2, then the correlation between (a- b) and (a+ b) is $(F^2 - s^2)/(F^2 + s^2)$. In principle, this correlation could be positive or negative but if F^2 is much larger than s^2, as suggested in Figure 3 below, then the intuitively appealing case emerges.

[4] Although, recently sellers in the United States have been observed listing their houses at a lower price and letting competing bidders drive the price upward from the listing price.

[5] For our data set, such a restriction would be significant since, of the houses in our data set that were sold, more than 9 percent of houses sold at a price that exceeded the list price. In Knight (2000), about 14 percent of houses sold at a price that exceeded the list price.

Because specification testing indicated the presence of heteroscedasticity, reported in Appendix Table A.1, the listing price model is estimated by generalized least squares (GLS).

Next, we specify the TOM model with TOM being a function of the characteristics of the house, market conditions and the listing price. Many authors have used ordinary least squares which is known to produce unbiased estimates. However, this method wastes information. For example in a "single risk" model, Lancaster (1990, ch 8.8) claimed that using a semi-log specification and ordinary least squares to estimate the determinants of TOM is equivalent to throwing away 39 percent of the data if the true model is exponentially distributed and 43 percent of the data if a Weibull distribution is more appropriate. In light of this, we estimate TOM using a hazard model with a Weibull specification of the baseline hazard function

$$f(t|\ X)= N\ 8(X)^{N}\ t^{N-1}\ \exp(-(8(X)*t)^{N}) \qquad (2)$$

if ***SOLD***= 1. We use a proportional hazards specification to explain the contribution of the independent variables where

$$8(X)= \exp(-X\$) \qquad (3)$$

We modify this likelihood in two ways. First, we assume that unmeasured heterogeneity in the hazard function can be described by a Gamma distribution with mean 1 and variance 2. Second, the observed time-on-the-market is the minimum of two random variables: the time-till-sale and the time-till-withdrawal. The fact that a seller can withdraw without selling introduces "censoring" into the duration data which misleadingly shortens the average time-on-the-market. Whether a seller is observed selling the house or withdrawing from the market depends on which of these events occurs first. For those houses which were withdrawn from the market at time t, i.e. ***SOLD***= 0, the probability that the TOM exceeds t is

$$1-F(t|\ X)= \exp(-(8(X)*t)^{N}). \qquad (4)$$

The maximum likelihood estimates of $, N and 2 correct for this random and frequent censoring. See Lancaster (1990) for further discussion.

Finally, a selling price model is estimated. ***DOP*** is predetermined when the buyer and seller eventually negotiate; thus, for houses which do sell, it can be used as a regressor in a semi-log specification of the sale price

$$E(\log(p^{S}))= X\ (+\ (_{1}\ \boldsymbol{DOP} \qquad (5)$$

One should note that this specification has an inherent flaw in that the selling price, p^S, and the listing price are highly correlated as the listing price, instead of bargaining power, may represent an unmeasured or omitted component of the house. Therefore, the use of a residual derived from a listing price equation as an independent variable in a selling price equation is likely to produce misleading estimates of bargaining power.[6] The fundamental problem is that we cannot separately identify the parameters of the listing price and selling price distributions. Because the solution to this problem is non-trivial, estimating the relationship between the selling price and the listing price while controlling for quality differences is the subject of a different paper.[7]

4. Description of data

The data pertain to single-family houses listed with the Arlington, Texas, Multiple Listing Service that went off market in 1997 as a result of either a sale or a withdrawal from the market.[8] The earliest observations were for houses initially offered for sale in the spring of 1996. Nearly all houses sold between December, 1996, and December, 1997. Table 1 summarizes the data.

Insert Table 1

More than half of the houses in the sample were sold and they sold at an average discount of 2.5 percent from their listing price. Of the houses that sold, the selling price exceeded the listing price in 9.3 percent of the cases. On average, the houses which sold had a lower list price ($102,687 versus $115,407), were slightly older (16.5 years versus 13.8 years) and smaller (1870 square feet versus 2015 square feet) than houses which were offered for sale and subsequently withdrawn. The withdrawn sample consisted of more newly constructed houses and houses under construction (6 percent versus 3 percent) than the sold sample.

Market conditions during the time period sampled suggest that the housing market was robust. Mortgage interest rates were decreasing: the FHA 30 year mortgage rate was at 8.58% in September 1996, a high for the year and decreased to 7.51% by the end of 1997. The mortgage rate for houses sold in the sample was 8.23% in September of 1996 and 7.67% in

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[6] For this reason, we cannot directly answer the important challenge posed by Sirmans, Turnbull and Dombrow (1995). By estimating the determinants of the sale price using information on TOM, on listings that sell without full exposure but not listing price, they argue that real estate markets are efficient enough to prevent the creation of abnormal gains and losses.

[7] The issue of omitted variables does not affect the analysis of TOM because our data set is drawn from the information that is presented to a buyer. Agents may be able to offer additional comments on specific houses but such comments would always be offered and do not negate the influence of the list price. On the margin, we are working with the same information as a buyer.

[8] The initial sample consisted of 4,256 houses. Some houses were missing data on the year built and square feet. These data were further trimmed to eliminate 382 observations that represented houses listed at either very high (greater than $250,000) or very low (less than $50,000) prices, instead of estimating separate equations based on an arbitrary segmentation of the market as done by some other authors. The final data set had 3,874 observations.

December of 1997. The average rate for houses sold was 8.03%. In addition, approximately 5.5 months of "inventory" was available for sale each month. (Inventory is calculated as the number of total listings in a month divided by the average number of sales per month over the last year.) The Real Estate Center at Texas A&M University suggests that a "seller's market" exists when inventory is less than 10 months. The average TOM was over 80 days but, if our data were restricted to houses that sold as in most other studies, the time-till-sale was relatively low at 59.9 days. The average TOM for properties that did not sell was 116 days.

Some of the variables used in the models were constructed. In the regressions, and in contrast to Table 1, the variables indicating the number of bedrooms or number of bathrooms are dummy variables to allow for a more flexible specification. The size of the property, ***Square Footage***, has been divided by 1000 to facilitate the computations. For the same reason, the age of houses was divided by 10. ***Time Listed*** represents the day the house is first listed. ***Time-Off*** represents the day when the house went off the market, either as a sale or a withdrawal. Both variables are scaled so that one year has elapsed if ***Time-Off*** - ***Time Listed*** = 1.

The variables, ***Spring***, ***Summer*** and ***Fall***, are used to account for seasonal variations in marketing time. In practice, a house may be offered during more than one season, especially for houses which are offered for a long duration. Therefore, these variables are defined to represent the *fraction* of the duration that took place during a particular season. ***Spring*** includes the months of April, May and June; ***Summer*** represents July, August and September; and ***Fall*** represents October, November and December. By constructing the variables in this fashion, the observed hazard rate is a weighted average of the seasonal hazard rates as implied by these variables. If a house is on the market during a single season, Spring for example, then ***Spring*** = 1, and ***Summer*** and ***Fall*** equal 0, and the hazard rate can be inferred directly. If a house is on the market across multiple seasons, then each season will have either a fractional value or a value of zero. This construction may bias the empirical estimates downward because the fraction of the marketing time spent in a season with a high sales rate tends to be less.[9]

Some of the variables are included to control for market conditions. The number of months of inventory, ***Inventory***, is used to measure changes in the balance of the supply and demand for housing. We use the number of ***Sales*** in a month and a measure of the mortgage interest rate, ***Rate***, as additional measures of the state of the market.[10]

The variables used to explain the listing price and the time-on-the-market are coded

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[9] Some authors (e.g. Yavas and Yang, 1995) have used a dummy variable to estimate the effect of seasonal variation. For each of the four seasons, the correlation between the variables created here and a dummy variable which equalled 1 in the season of initial listing is about 0.6.

[10] Studies of the "Beveridge Curve" (e.g. Blanchard and Diamond, 1989) in labor markets suggest that there may be a better measure but constructing such a measure requires information on the flow of active buyers and such information is extremely hard to obtain.

differently to account for differences between the month in which a house is initially listed and the month in which it is sold or withdrawn. Specifically, in Table 2, the suffix ***On*** indicates the data is taken from the listing month. The absence of a suffix indicates either that an average is being used or that the variable is constant over time.

For each house, ***Sighat*** is the estimated weight used to correct for heteroscedasticity in the listing price equation, i.e. the predicted standard deviation, and is based on the coefficients reported in Table A.1.[11] This variable also identifies the types of houses with an unusually high or low variance of listing price, presumably due to omitted variables that are correlated with other characteristics of a house. We divide the sample into the 30 percent of the sample with the highest values of ***Sighat*** and the 30 percent with the lowest values of ***Sighat*** and construct two variables, ***Low*DOP*** and ***High*DOP***, by multiplying indicator variables for each subsample by ***DOP***. The variables are constructed this way to reduce the problem of multicollinearity since ***Sighat*** is constructed from X and is correlated with the other regressors in the TOM equation.

5. Results

The results for the listing price model are shown in Table 2. Most of coefficients are statistically significant at the 5 percent level or better. Nearly 90 percent of the variation in the log of the list price is explained by the model. Interestingly, listing prices are not shown to significantly vary by season and, of the three market-oriented variables, only ***Sales*** was significant suggesting increasing listing prices with increasing sales volume. The results show that physical and locational characteristics seem to dominate the determinants of the listing price.

Insert Table 2

The primary purpose in running the list price model was to create ***DOP***. By looking at ***DOP***, it is clear that list prices differ between houses which eventually sell and those that are withdrawn. The mean value of ***DOP*** for houses that sold is -0.0139 (i.e. ceteris paribus, the list price of such houses was 1.39 percent less than the average). For houses which were withdrawn, the mean is 0.0171, or 1.71 percent above the average. This difference in means produces a test statistic of 7.9 which is significant at beyond the 0.01 percent level. Figure 2 illustrates this difference by comparing the cumulative distributions of ***DOP*** for houses which eventually sold and for those which did not, with the exception of the highest and lowest deciles.[12] The standard

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[11] We assume that heteroscedasticity in the list price equation would be described by an exponential function and, using the residuals to an OLS regression, e, we identified which characteristics of a house were statistically significant in explaining variation in $\log(e^2)$. If f represents the fitted value derived from this regression, then ***Sighat***= $(\exp(f))^{1/2}$ and can be used to reestimate $\log(p^L)$ using GLS.

[12] Figure 3 represents the decile values between 10 and 90 and is trimmed to omit the maximum and minimum observations in each distribution. The maximum and minimum values

deviation of ***DOP*** for each sample (sold or withdrawn) is much larger than the difference between the means. The former is presumably due to omitted variables while the latter primarily indicates an attempt to exert bargaining power as evidenced by the threat to withdraw if no buyer offers an acceptable price. A similar but smaller difference exists between samples for houses which were sold quickly and those which lingered on the market.

Insert Figure 2 and Figure 3

An initial look at the TOM relationship is pictured in Figure 3, which shows how the hazard rates, not conditioned on explanatory variables, vary with duration for the first 20 weeks. The average probability of sale during a week is about 5 percent. On the other hand, the per-week probability that a seller withdraws before selling rises with duration. The two spikes on the withdrawal hazard rates occur during days 94 to 96 and during days 123 to 127 after the listing agreement was signed. By the twentieth week, only 18.6 percent of the sample remains on the market. The spikes are not easily explained. Even though they occur just after the end of three months and just after the end of four months, the timing does not seem to correspond to the expiration of listing contracts. For the subset of the sample that provides an expiration date, the average number of days from the list date until expiration of the listing contract was approximately 156 days. This average holds true for properties that were sold and those that were withdrawn.

Insert Table 3

The results for the hazard model of TOM (see Table 3) show that most, but not all, of the coefficients representing housing characteristics are statistically insignificant in explaining the time-on-the-market. In each case, when a reported coefficient is positive then an increase in the associated variable tends to increase the expected time required to sell a house, or equivalently, decrease the instantaneous hazard rate.

In support of the theory, the coefficients on ***DOP*** shows that an increase in the list price increases the expected TOM at an increasing rate. At ***DOP***= 0, a one percent increase in the list price increases the average TOM by 1.3 percent. The positive and significant coefficient on ***Low*DOP*** reveals that houses in a market segment with a low variance of listing price are more sensitive to deviations from the expected listing price. If the listing prices of comparable houses are tightly grouped, then a seller of one house who chooses a list price outside normal or "established" bounds increases the risk that potential buyers will not visit and increases the expected marketing time. Data analysis shows that houses in the sample having a low variance

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are extreme observations and are extremely sensitive to a random event. In contrast, even the 10^{th} percentile of each distribution depends on the realization of about 200 random variables.

Notice also that the difference between the distributions remains even though the average unsold house was on the market for a longer duration and, presumably, represents one or more unrecorded decreases in the list price.

of listing prices tend to be smaller and newer than the average house.

The results for the TOM model also demonstrates that the effect of changing market conditions is very important. This is most evident with ***Inventory***, which shows that an increase in the ratio of listings to sales lengthens the TOM for a particular seller. As a surprise to few, ***Winter*** is the season with the highest expected TOM. It may surprise some readers that there is no significant difference in TOM between ***Winter*** and ***Spring*** although there is a difference between those seasons and ***Summer*** and ***Fall***. The estimated coefficient for duration dependence, N, is significant with a value less than one indicating that an increase in duration increases the probability of sale during the next interval of time.[13]

The statistical significance of the location variables is economically significant. Consider the three locations with statistically significant coefficients in both Tables 2 and 4 using the relatively weak 10 percent standard. Each location with above average list prices has below average TOM, and vice versa. Determining whether this phenomenon is persistent requires a longer data series.

Insert Table 4

Table 4 reports on the coefficients produced when estimating the selling price function using OLS and the heteroscedasticity correction referred to earlier. This regression is comparable to the familiar hedonic price function which assumes that the price of a house is determined by its characteristics and omits indicators of market conditions, other than the passage of time. Not surprisingly, most of the coefficients are significant and have about the same magnitude as with the list price equation, with the exception of the coefficients showing the value of the number of bedrooms.

The selling price discount is easy to calculate [1- selling price/ listing price] and is often used by real estate professionals to indicate changing market conditions because it automatically controls for omitted variables that affect the listing price and selling price simultaneously and, hopefully, equally. To gain insight into the relationship between ***DOP*** and the selling price discount, we restrict our attention to the subsample of houses that sold. A simple OLS regression of the discount on ***DOP*** and a constant produces $R^2 = 0.0059$. Our model contains no particular predictions about this relationship. In fact, it is difficult to imagine that there would be a general prediction. For example, if a 1 percent increase in the list price led to a 1 percent increase in the sale price, on average, then the only source of variation in discount would be random (i.e. the identity of the buyer). This example is not entirely unreasonable since the cost

[13] The estimate N should be interpreted carefully since it may combine the effects of ordinary duration dependence in the sale process, such as stigma or other effects such as those hypothesized and generally rejected by Sirmans, Turnbull and Dombrow (1995), and the effects of time-dependent decreases in the list price, as documented by Knight (2000) and Ortola-Magne and Merlo (2000). Resolving this problem is a matter of on-going research.

of a tougher bargaining strategy appears as an independent dimension: TOM. An increase in the expected TOM decreases the likelihood that the house would be included in the sold subsample.

6. Conclusion

This paper proposes a model for analysing the relationship between the list price, the sale price and the time-on-the-market (TOM). The theoretical model shows that one should recognize that there is no direct trade off between the sale price and TOM but that market conditions generate a locus which describes how the expected sale price and the expected TOM vary jointly based on the choice of the list price. The empirical analysis uses two stages to estimate a kind of reduced form where the first stage estimates deviations from the typical list price and the second stage studies the contribution of these deviations to explaining time on market and the sale price.

We found that increases in the list price increase TOM at an increasing rate and that the effect is magnified for the type of houses with a low variance of list prices. An increase in the inventory lengthens TOM for an individual seller. An Appendix demonstrates the benefits of recognizing that TOM is censored for the many potential sellers who withdraw before selling. Our model predicts a relationship between the listing price and the selling price that would complement the predictions about TOM but an identification problem prevents estimating that relationship: in practice, the list price represents a combination of a seller's bargaining power and unmeasured characteristics of a house. Figure 3 indicates the seriousness of this problem since the standard deviation of each distribution is larger than the difference between the distributions. We found that the discount from list price, for those houses where a buyer and seller agreed on a price, is almost uncorrelated with deviations in the list price.

Our analysis points to at least two important questions that should be resolved. Unravelling the identification problem in the sale price equation can refine the analysis by showing the direct effects of bargaining power. Anglin (1999) uses survey data from a different city and different time to estimate that the average difference between a seller's reservation value and a buyer's reservation value, i.e. the surplus to be divided by bargaining, is about 3.5 percent of the list price. It would be useful to check whether these estimates are consistent. Secondly, our analysis shows that censoring of the sale process by withdrawals affects the estimates. Figure 2 shows spikes in the unconditional hazard rate of withdrawals around day 95 and day 125. By themselves, the spikes are not easily explained. Careful analysis of the withdrawal process as a whole requires a different methodology as well as additional data analysis to determine whether the same houses and sellers reappear in the data set with a different real estate broker.

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Appendix

A.1 Heteroscedasticity Analysis

Table A.1 shows the determinants of heteroscedasticity in the list price and sale price equations.[14] The same set of regressors is used to explain heteroscedasticity in both equations. The use of ***BD2***, ***BTH1*** and ***BTH3*** as regressors indicates that the heteroscedasticity is segment-specific rather than being monotonically related to the number of bedrooms or bathrooms. The magnitudes of the coefficients in each regression are, in general, roughly equal and the explanatory power of each regression is low.

Insert Table A.1

A.2 Alternate TOM Models

This paper discusses new explanatory variables and suggests a new method of analysing the determinants of TOM. To recognize the separate contribution of each idea, this section of the Appendix compares our proposed statistical methodology to other commonly-used methods. The first two columns of Table A.2 report our findings for the determinants of TOM using ordinary least squares (OLS) with ***log(t)*** as the dependent variable using only the data on houses that were sold. The second two columns use the same data and report on the estimates derived from a Weibull model with heterogeneity correction but without correcting for censoring. These results can be compared to the estimates based on our preferred specification reported in Table 4.

Insert Table A.2

In the OLS specification, most of the coefficients on characteristics are not statistically significant, which would support a hypothesis that the expected TOM is equalized across segments of this residential housing market. The low levels of statistical significance would be expected of an inefficient estimation methodology.

The second specification indicates the kind of differences that might be apparent when using a better methodology than OLS. Even so, these estimates find no evidence of unmeasured heterogeneity whereas Table 3 indicates that heterogeneity is a significant feature. Comparing Table A1 and Table 3 shows that the absolute value of all of the coefficients on market conditions increases when the methodology recognizes censoring, and that the coefficients on ***SALE*** and ***RATE*** become statistically significant. Therefore, the choice of econometric methodology would affect any conclusion that the market has reached an equilibrium.

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[14] The constant in each regression represents a three-bedroom house with two bathrooms in area 85. According to whether the dependent variable is the list price, TOM or the sale price, the constant also represents the effect of being listed, on the market or sold during the Winter season.

Table 1: Descriptive Statistics: Means, standard deviations and t-test for differences between the means for sold and withdrawn houses.

	Sold Houses n=2104		Withdrawn Houses n=1770		
Variable	Mean	Std.Dev.	Mean	Std.Dev.	T-test
List Price	102,687	40,546	115,407	44,997	9.17
Selling Price	100,259	39,306	-	-	-
Square Feet	1870.2	565.3	2015.6	604.5	7.69
Age (in years)	16.49	10.28	13.81	9.45	-8.42
Bedrooms	3.30	0.55	3.38	0.55	4.60
Bathrooms	2.19	0.48	2.28	0.51	5.59
Pool (1=yes;0=no)	0.15	0.36	0.12	0.33	-2.57
Fireplace (1=yes;0=no)	0.89	0.31	0.93	0.26	4.24
Stories (number of stories)	1.19	0.39	1.30	0.47	7.70
No Garage (1=no garage; 0 = garage)	0.02	0.15	0.09	0.28	8.40
Under Construction (1=yes; 0=no)	0.01	0.11	0.02	0.15	2.15
New Construction (1=yes;0=no)	0.03	0.16	0.04	0.19	2.14
MLS Area 82 (1 if located in Area 82; 0 if not)	0.11	0.32	0.09	0.29	-2.37
MLS Area 83 (1 if located in Area 83; 0 if not)	0.11	0.31	0.07	0.25	-4.03
MLS Area 84 (1 if located in Area 84; 0 if not)	0.04	0.20	0.03	0.16	-2.12
MLS Area 85 (1 if located in Area 85; 0 if not)	0.21	0.41	0.21	0.41	-0.31
MLS Area 86 (1 if located in Area 86; 0 if not)	0.10	0.30	0.06	0.24	-4.45
MLS Area 87 (1 if located in Area 87; 0 if not)	0.22	0.42	0.32	0.47	6.82
MLS Area 88 (1 if located in Area 88; 0 if not)	0.21	0.41	0.23	0.42	1.26
Rate-On (Market interest rate observed in the month the property went on the market)	8.07	0.11	8.09	0.11	3.03
Volume (Average number of MLS sales over the six months prior to the listing date)	2.94	0.71	2.90	0.69	-1.58
Inventory (Number of houses available for sale divided by the monthly sales for the month the property went on the market)	5.87	0.75	6.09	0.93	7.92

T	59.47	53.82	112.85	70.71	26.04
DOP	-0.014	0.11	0.02	0.13	7.88
Sighat	0.06	0.01	0.06	0.02	6.48
Low*DOP	-0.00	0.05	0.01	0.05	5.95
High*DOP	-0.00	0.07	0.01	0.09	4.05
Winter (percentage of the marketing time in)	0.24	0.37	0.23	0.30	-1.29
Spring (percentage of the marketing time in)	0.30	0.40	0.26	0.31	-4.07
Summer (percentage of the marketing time in)	0.27	0.38	0.27	0.32	0.29
Fall (percentage of the marketing time in)	0.19	0.32	0.24	0.32	5.61

TABLE 2: Determinants of List Price: Using the heteroscedasticity correction reported in Table A.1; the dependent variable is log(list price)

Variable	Coefficient	T-Statistic	Variable	Coefficient	T-Statistic
Constant	10.96	29.76	***MLS Area 82***	0.11	14.32
Square Feet	0.75	24.83	***MLS Area 83***	0.05	5.34
Square Feet - SQ	-0.11	-13.15	***MLS Area 84***	-0.14	-9.86
Age	-0.12	-9.63	***MLS Area 86***	-0.15	-16.96
Age - SQ	0.02	9.47	***MLS Area 87***	0.01	1.15
2 Bedroom	-0.03	-1.34	***MLS Area 88***	-0.09	-11.61
4 Bedroom	0.05	1.82	***Square Feet x Baths***	0.09	4.95
5 Bedroom	0.08	1.31	***Square Feet x No garage***	-0.05	-4.07
1 Bath	-0.01	-0.16	***Bedrooms x Bathrooms***	-0.02	-2.15
1.5 Bath	-0.02	-0.95	***Square Feet x Age***	-0.04	-8.80
2.5 Bath	0.00	0.18	***Age x Stories***	0.05	7.49
3 Bath	-0.02	-0.36	***Age x No Garage***	-0.04	-6.44
3.5 Bath	-0.07	-0.89	***Time-Listed***	0.01	0.45
4 Bath	-0.20	-1.67	***Inventory-On***	-0.00	-0.13
Pool	0.09	15.20	***Sales-On***	0.02	2.95
Fireplace	0.02	2.40	***Rate-On***	-0.05	-1.01
Stories	-0.12	-10.58	***Spring-On***	-0.00	-0.17
No Garage	0.14	4.16	***Summer-On***	-0.03	-1.66
New Construction	0.05	3.75	***Fall-On***	-0.01	-0.64
Under Construction	0.01	0.35			

*** Number of Observations = 3874; Adjusted-R^2 = 0.89**

Table 3: Determinants of Time-on-the-Market (TOM)

Variable	Coefficient	T-Statistic	Variable	Coefficient	T-Statistic
Constant	31.40	4.71	***MLS Area 82***	-0.26	-3.01
Square Feet	0.34	1.13	***MLS Area 83***	-0.31	-3.08
Square Feet - SQ	0.01	0.19	***MLS Area 84***	-0.08	-0.52
Age	-0.12	-1.43	***MLS Area 86***	-0.12	-1.30
Age - SQ	-0.00	-0.18	***MLS Area 87***	0.22	3.14
2 Bedroom	-0.33	-1.98	***MLS Area 88***	0.14	1.81
4 Bedroom	-0.07	-1.11	***Spring***	0.08	0.47
5 Bedroom	-0.37	-2.13	***Summer***	-0.51	-2.41
1 Bath	0.27	1.75	***Fall***	-0.63	-2.92
1.5 Bath	-0.29	-1.77	***Inventory-On***	1.07	8.48
2.5 Bath	0.02	0.18	***Sales-On***	0.22	2.00
3 Bath	0.03	0.27	***Rate-On***	-4.24	-4.62
3.5 Bath	0.11	0.63	***DOP***	1.30	4.18
4 Bath	0.03	0.10	***DOP***^{2}	1.98	2.07
Pool	-0.19	-2.85	***Low*DOP***	1.94	3.48
Fireplace	-0.07	-0.75	***High*DOP***	-0.41	-0.95
Stories	0.25	3.32	2	0.84	6.12
No Garage	1.16	8.55	N	0.77	26.83
New Construction	0.06	0.42			
Under Construction	0.36	1.70			

*** Number of Observations = 3874; Log-L = -4641.03; Log-L (\$= 0) = -5477.05**

Table 4: Determinants of Sale Price: Using the heteroscedasticity correction reported in Table A.1; dependent variable = log(selling price))

Variable	Coefficient	T-Statistic	Variable	Coefficient	T-Statistic
Constant	10.67	106.47	***MLS Area 82***	0.13	13.34
Square Feet	0.75	18.44	***MLS Area 83***	0.07	6.34
Square Feet - SQ	-0.11	-9.16	***MLS Area 84***	-0.13	-7.76
Age	-0.08	-4.87	***MLS Area 86***	-0.13	-11.26
Age - SQ	0.01	5.58	***MLS Area 87***	0.01	0.74
2 Bedroom	-0.13	-4.27	***MLS Area 88***	-0.08	-7.73
4 Bedroom	0.11	3.21	***Time-Off***	0.01	0.70
5 Bedroom	0.21	2.52	***Square Feet x Baths***	0.10	4.06
1 Bath	-0.05	-1.02	***Square Feet x No garage***	-0.10	-2.98
1.5 Bath	-0.05	-1.59	***Bedrooms x Bathrooms***	-0.05	-3.48
2.5 Bath	0.05	1.54	***Square Feet x Age***	-0.05	-8.10
3 Bath	0.06	0.95	***Age x Stories***	0.04	4.11
3.5 Bath	0.03	0.26	***Age x No Garage***	-0.03	-2.45
4 Bath	-0.03	-0.19			
Pool	0.11	13.82			
Fireplace	0.02	1.45			
Stories	-0.12	-7.63			
No Garage	0.16	1.87			
New Construction	0.07	3.58			
Under Construction	0.04	1.57			

*** Number of Observations = 2104; Adjusted R^2 = 0.89**

Table A.1: Determinants of Heteroscedasticity

	List Price Equation		Sale Price Equation	
Variable	Coefficient	T-statistic	Coefficient	T-statistic
Constant	-7.12	-34.68	-7.11	-24.12
Square Feet	0.46	5.09	0.47	3.67
Age	0.15	3.36	0.17	2.85
2 Bedroom	0.70	2.53	0.70	2.01
1 Bath	-0.29	-1.18	-0.78	-2.37
3 Bath	-0.21	-1.55	-0.39	-2.01
No Garage	0.57	3.38	0.93	2.68
Stories	0.32	3.12	0.26	1.69
MLS Area 86	-0.16	-1.11	-0.55	-3.05
MLS Area 88	-0.50	-4.74	-0.47	-3.10

*** Number of Observations = 3874; Adjusted R^2 = 0.04**

Table A.2: Alternative Estimates of the Determinants of Time-on-the-Market
(using only the data on sold houses)

	Log-linear OLS		Weibull w/o censoring	
Variable	Coefficient	T-statistic	Coefficient	T-statistic
Constant	1.84	0.30	2.14	0.33
Square Feet	0.07	0.25	-0.07	-0.26
Square Feet-SQ	0.04	0.65	0.06	0.95
Age	-0.15	-1.83	-0.09	-1.20
Age-SQ	0.02	0.80	0.01	0.80
2 Bedroom	-0.06	-0.41	-0.19	-1.44
4 Bedroom	-0.07	-1.09	-0.05	0.92
5 Bedroom	-0.20	-1.21	-0.03	-0.19
1 Bath	0.05	0.37	0.15	1.31
1.5 Bath	-0.09	-0.60	-0.15	-1.12
2.5 Bath	0.04	0.51	0.06	0.77
3 Bath	0.08	0.82	0.06	0.62
3.5 Bath	0.06	0.32	0.01	0.06
4 Bath	0.15	0.52	-0.22	-0.74
Pool	0.01	0.13	0.01	0.18
Fireplace	-0.16	-1.75	-0.07	-0.96
Stories	0.10	1.40	-0.00	-0.02
No Garage	0.12	0.85	0.11	0.83
New Construction	-0.24	-1.56	0.34	2.60
Under Construction	-0.10	-0.49	0.27	1.41
MLS Area 82	-0.09	-1.16	-0.19	-2.68
MLS Area 83	-0.25	-2.57	-0.28	-3.68
MLS Area 84	0.04	0.30	-0.17	-1.39
MLS Area 86	0.03	0.36	-0.06	-0.82
MLS Area 87	0.12	1.80	0.02	0.29

MLS Area 88	0.16	2.08	0.04	0.52
Spring	-0.25	-1.67	-0.28	-1.68
Summer	-0.18	-0.88	0.15	-0.69
Fall	0.01	0.05	-0.13	-0.63
Inventory	0.49	4.09	0.52	4.29
Sales	0.03	0.30	0.01	0.09
Rate	-0.13	-0.15	-0.10	-0.11
DOP	0.09	0.28	-0.16	-0.71
DOP- SQ	-2.05	-2.06	0.69	0.88
Low*DOP	0.96	1.88	1.15	2.60
High*DOP	-0.55	-1.29	-0.08	-0.23
2	--	--	0.00	0.00
N	--	--	0.79	29.31

*** Number of Observations = 2104. OLS Model: R^2= 0.12; Weibull Model: Log-L = -2813.69 and Log-L ($= 0)= -3021.56.**

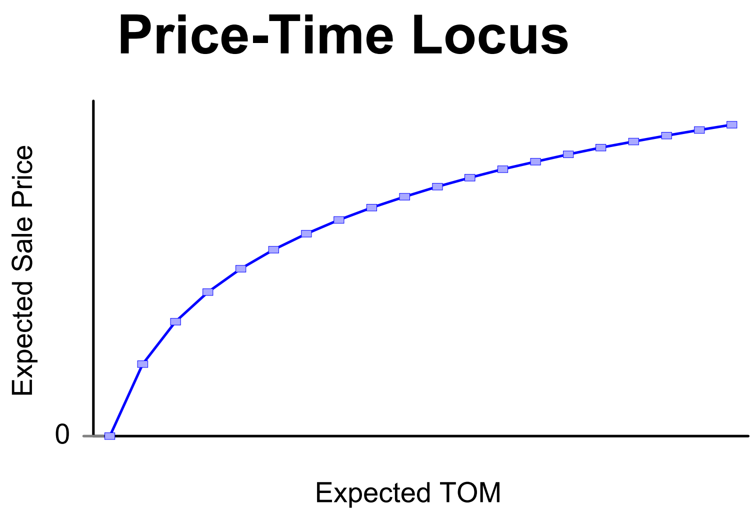

Figure 1

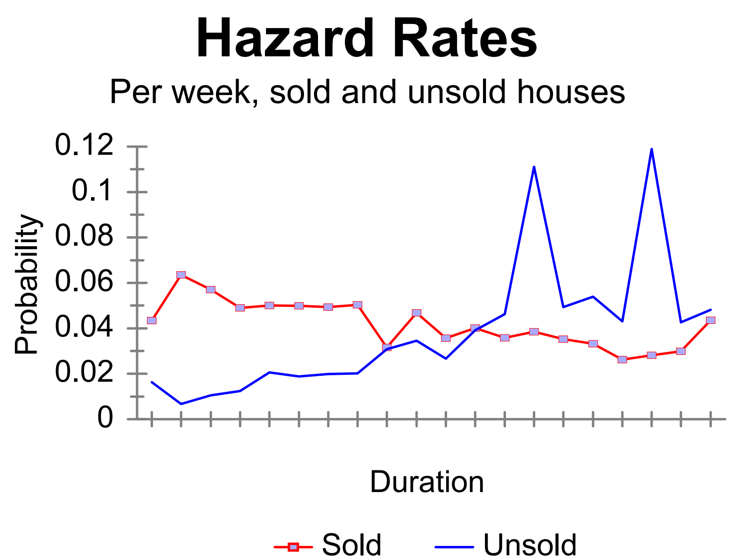

Figure 2

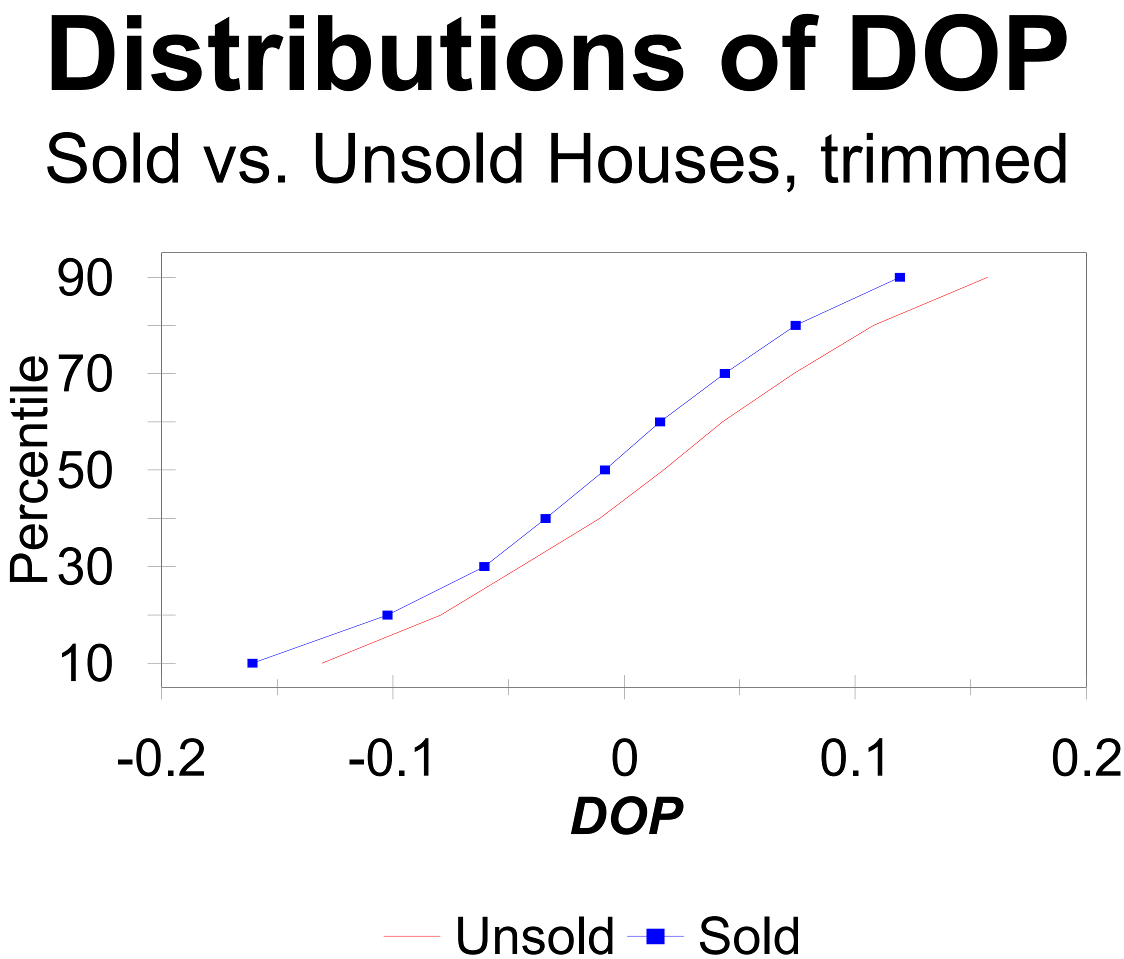
Distributions of DOP
Sold vs. Unsold Houses, trimmed
90
70
50
30
10
Percentile
-0.2
-0.1
0
0.1
0.2
DOP
Unsold
Sold

Figure 3