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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 the 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 an increase in the list price increases expected time-on-the-market (TOM). Because house buyers must solve a type of signal extraction problem, the effect of a higher list price is magnified for houses in a market segment having 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 This paper also shows that the list price of houses which are withdrawn before sale has a higher mean and variance, and that the possibility of withdrawal censors information about the time-on-the-market.

Key Words: list price, over-pricing, duration model, sale price, hedonic price function, liquidity, bargaining power, search, matching, time-on-the-market, time-till-sale, withdrawal, censoring, omitted variables

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 seller's initial choice of list price 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. Conversely, if the initial price is too low, the seller may effect a quick sale at the expense of selling the property for less than could have been received with better market exposure.

Beginning with the premise that time-on-the-market (TOM) depends on the list price because the list 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 list price acts as a signal to potential buyers, providing information to a potential buyer that facilitates the narrowing of the buyer's search to houses in his specific price range. From the seller's perspective, if the list price is substantially higher than the expected list price, then a prospective buyer is less likely to visit the house. One of the critical elements of this model is the degree of overpricing (*DOP*), measured as the percentage difference between the actual list price and the expected list price given the observable characteristics of the house. We hypothesize that houses with a smaller *DOP* will sell faster. Also, any effect of an increase in *DOP* is magnified for houses in a market niche having a smaller list price variance.

A large data set allows us to identify both properties that were eventually sold and those that were withdrawn from the market. By including ''withdrawn'' houses in the TOM 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 expected TOM. Generally, TOM varies more with spatial location and market conditions than it does with property characteristics. We also show that the list price and the selling price functions are not identical, suggesting they have separate roles in the housing transaction process, and that the ratio of the selling price to list price has little relationship with *DOP*.

2. Background

The sequence of events prior to the sale of a house is generally well understood. Most sellers contract with a broker who helps to choose a list price. This price is observed by prospective buyers who use this information in combination with their preferred price ranges to determine which houses to include in the sample of houses they will inspect. Eventually, one or more of the possible buyers, who may have entered the market at any time, makes a bid.

This simple approach offers no direct connection between the selling price and TOM. Any linkage between a selling price and TOM may be further obscured because both are randomly determined by matching and bargaining processes in the market. Thus, it is preferable to describe market forces as creating an upwardly sloping locus of expected selling price-expected TOM combinations.[1] This locus defines a ''budget constraint'' on the set of feasible outcomes for expected selling price and expected TOM. Given the trade-off between price and TOM, along with his specific risk tolerance, an individual seller chooses a list price.

Economic 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, for example, Wheaton, 1990; Yavas, 1992). One can also argue that a buyer who searches more intensely has a higher probability of finding a low-priced house of specified quality (see, for example, Anglin, 1997). Also, houses that remain on the market for an overly long time period can become stigmatized, because current buyers assume that previous buyers must have discovered a non-trivial problem associated with the house. Taylor (1999) formally studies this issue.

Arnold (1999) uses a search-and-bargaining model in a theoretical treatment of the optimal list price. In his model, the list 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. 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 on the list price of seller motivation. They also propose that the price-TOM relationship should include the effects of the effort level chosen by brokers. Given the complexity of this strategic interaction, a change in the list price may have an ambiguous effect on TOM (see p. 356) and, therefore, the price-TOM locus may slope downward for an interval. Even so, rational choice by a seller implies that only the upward sloping portions are relevant. Their empirical analysis demonstrates that higher list prices lead to longer marketing times. These studies firmly establish the role of the list price in attracting potential buyers to a property and in the effort a broker will contribute to the marketing of a property.

An understanding of the role of asset atypicality is crucial to a study of housing market dynamics. Haurin (1988) introduces the importance of asset atypicality, measuring the difference between a given house and an appropriately defined ''typical'' house, as the driving force in explaining the variation in the marketing times of housing. Atypical houses are more difficult to market and thus function in a thinner market. Haurin confirms this hypothesis showing that atypicality increases TOM.

Closely related to asset atypicality is liquidity. Generally, housing segments that are more homogenous are expected to have greater liquidity. Kluger and Miller (1990) define a liquidity measure that estimates the differences in marketing time between houses with differing characteristics and study relative liquidity using a hazard model. Housing characteristics, excepting age, are mostly insignificant in explaining TOM. Forgey et al. (1996) extend this research and show that TOM is explained by the age and size of the house as well as various market-related variables. They also show that sellers of house types expected to sell faster benefit from the increased liquidity. In his theoretical analysis of liquidity, Krainer (2001) shows that both the selling price and the probability of sale are positively correlated with the flow of buyers. Interestingly, the price under poor market conditions does not fully adjust because of the seller's valuation of the option of waiting to sell in the future with improved market conditions.

Another critical component to 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 list price, pointing out that the list price may serve as a signal of a seller's patience. Ong and Koh (2000) find that the expectation of capital gains increases the average TOM. Springer (1996) looks at the impacts of seller motivation on TOM and finds that various market and seller characteristics, including an overpricing measure, were significant in explaining TOM. Overpricing, measured as the ratio of the list price to the expected selling price, is shown to extend marketing times, indicating lower motivation (greater patience) on the part of the seller. Glower et al. (1998), using a hazard model, also look at the impact of seller motivations on TOM and find that sellers with either new jobs or specified moving dates have the largest influences on marketing time. In some ways, our work extends the analysis of their variable, *Percent Listing Error I*.

Finally, Knight (2002) looks at the impact of changes to the list price.[2] Using two-stage least squares and focusing on the effect of changes in the ''mark-up'' (i.e., list price/selling price − 1), his results show the impact of listing a house ''too high'' and then revising the list price. Specifically, homes whose list 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 or not the initial or the final list price is used, although the direction of this effect appears to depend upon how duration is measured.

3. Model and methodology

3.1. Theoretical model

The price-TOM locus represents the effects of a seller's choices and, together with the seller's motivation embodied in his objective function, one can solve for the optimal list price. For a given type of house, described by X, the list price (p^{L}) is 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, that is E(TOM), must also increase. Thus it is imprecise to talk about ''optimal TOM'' or ''optimal selling price,'' as though either can be chosen directly, because each of these concepts ignores half of the trade-off that makes a particular list price optimal.

Changes in X may shift the price-time locus and change the optimal list price. This shift occurs for two reasons. The obvious reason is that houses with differing X attract different numbers of and types of buyers. Given that the trade-off exists, there is a second reason to expect TOM to depend on X. To illustrate, consider two sellers with the same taste but the first seller's house receives a higher valuation from potential buyers. Suppose that the price-TOM locus of the seller of the more valuable house has a parallel upward shift relative to that of the second house. Assuming that both a higher price and a shorter TOM are ''normal goods,'' the first seller would take advantage of his advantageous position by selling at a higher price, but the increase should be less than increase in the buyers' willingness to pay. The seller also benefits by selling in less time. Thus both the selling price and TOM should depend on X.

A 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 market segment. But, because buyers have an incomplete prior description of a house, an inspection may reveal more information. Thus, a house may be listed higher than its apparent peer group because of features only revealed through inspection. However, a high list price may also indicate an attempt by the seller to exert bargaining power that adversely affects the potential buyer. 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 the list price can be expected to have less effect on the behavior of a group of potential buyers.

This mechanical treatment of the housing 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 problem facing buyers and sellers does not change but 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 selling price cannot exceed the list price. This assumption is regularly falsified.[5]

3.2. Methodology

The first step in the analysis is to estimate the typical list price for a house described by X under market conditions described by M. The list price (p^{L}) model is:

$$E(\log(p^{\mathrm{L}})) = X\alpha_X + M\alpha_M. \tag{1}$$

Because specification testing indicated the presence of heteroscedasticity, the list price model is estimated by generalized least squares (GLS). The residual of the list price model is used to estimate the degree of overpricing, *DOP*, the percentage deviation from a ''typical'' list price for a house described by X and M. *DOP* is calculated as $\log(p^{\mathrm{L}}) - E(\log(p^{\mathrm{L}}); X, M)$. *DOP* is expected to affect the eventual selling price, p^{S} and the TOM.

Next, we specify the TOM model with TOM being a function of the characteristics of the house, market conditions and the list price. Many researchers have used ordinary least squares (OLS) to estimate a TOM model. This method is known to produce unbiased estimates, but is also known to waste information. For example in a ''single risk'' model, Lancaster (1990, chapter 8.8) claims that using a semi-log OLS model 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 fact, we estimate TOM using a hazard model with a Weibull specification of the baseline hazard function[6]

$$f(t \mid X, M, DOP) = \varphi\lambda(X, M, DOP)^{\varphi} t^{\varphi - 1} \exp(-(\lambda(X, M, DOP)^{*} t)^{\varphi}) \tag{2}$$

where φ is a duration dependency parameter, λ is a scaling parameter, t is TOM, and other variables are as previously described. We use a proportional hazards specification to explain the contribution of the independent variables where

$$\lambda(X, M, DOP) = \exp(-X\beta_X - M\beta_M + g(DOP)) \tag{3}$$

for some function $g(.)$.

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

θ. Second, the observed TOM is the minimum of two random variables: the-time-till-sale and the time-till-withdrawal. Whether a seller is observed selling the house or withdrawing from the market depends on which of these events occurs first. The fact that a seller can withdraw without selling introduces ''censoring'' into the duration data which misleadingly shortens the average TOM. The variable, *Sold*, is a binary variable indicating whether a property was sold $(Sold = 1)$ or withdrawn. For those houses which were withdrawn from the market at time t, the probability that the time-till-sale exceeds t is

$$1 - F(t \mid X, M, DOP) = \exp(-(\lambda(X, M, DOP)^{*} t)^{\varphi}). \tag{4}$$

The maximum likelihood estimates of β, φ and θ correct for this random and frequent censoring. See Lancaster (1990) for further discussion.

Finally, a selling price (p^{S}) model is estimated. *DOP* is determined weeks or months before a buyer and seller negotiate over the selling price; thus, for houses that sell, it can be used to explain the selling price (p^{S}) without fear of introducing simultaneity bias. The selling price model is:

$$E(\log(p^{\mathrm{S}})) = X\gamma + \gamma_1 DOP. \tag{5}$$

One should note an inherent flaw in this specification in that the selling price and the list price are highly correlated because both prices include the effects of unmeasured or omitted characteristics of a house. Therefore, the use of a residual from a list price equation as an independent variable in a selling price equation may produce misleading estimates of bargaining power. A basic problem is that we cannot separately identify the parameters of the list price and selling price distributions. Because the solution to this problem is non-trivial, estimating the relationship between the selling price and the list 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 are 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.

More than half of the houses in the sample were sold,[9] selling at an average discount of 2.5 percent from their list price. Of the houses that sold, 9.3 percent sold for a price in excess of the listing price. On average, the houses which sold had a lower list price ($101,511 versus $113,570), were slightly older (17.2 years versus 14.7 years) and smaller

Table 1. Descriptive statistics: means, standard deviations and *t*-tests for differences between the means for sold $(N = 2{,}022)$ and withdrawn $(N = 1{,}663)$ houses.

	Sold Houses		Withdrawn Houses		
	Mean	Std. Dev.	Mean	Std. Dev.	*t*-Statistic
List Price	101,510.59	39,968.71	113,569.68	44,812.22	– 8.53
Selling Price	99,070.60	38,702.00	n/a	n/a	n/a
Square Feet (/1,000)	1.86	0.57	2.00	0.61	– 7.18
Age (in years /10)	1.72	0.99	1.47	0.91	7.83
Bedrooms	3.30	0.55	3.37	0.55	– 4.02
Bathrooms	2.18	0.49	2.27	0.51	– 5.54
Pool (1 = yes; 0 = no)	0.16	0.36	0.13	0.34	2.30
Fireplace (1 = yes; 0 = no)	0.89	0.32	0.93	0.26	– 4.37
Stories (number of stories)	1.19	0.39	1.30	0.47	– 7.68
No Garage (1 = no garage; 0 = garage)	0.02	0.16	0.08	0.28	– 7.73
MLS Area 82 (1 if in Area 82; 0 if not)	0.12	0.32	0.09	0.29	2.58
MLS Area 83 (1 if in Area 83; 0 if not)	0.11	0.31	0.07	0.26	3.80
MLS Area 84 (1 if in Area 84; 0 if not)	0.04	0.20	0.03	0.16	2.42
MLS Area 85 (1 if in Area 85; 0 if not)	0.21	0.41	0.21	0.41	0.07
MLS Area 86 (1 if in Area 86; 0 if not)	0.10	0.31	0.06	0.25	4.42
MLS Area 87 (1 if in Area 87; 0 if not)	0.22	0.41	0.31	0.46	– 5.97
MLS Area 88 (1 if in Area 88; 0 if not)	0.19	0.40	0.22	0.42	– 2.22
Time Listed	1.47	0.30	1.39	0.34	7.13
Rate-On (Observed market interest rate when, the property went on the market)	8.07	0.11	8.08	0.11	– 2.66
Sales (Average number of MLS sales over the 6 months prior to the listing date /100)	2.93	0.70	2.91	0.69	1.03
Inventory-On (Houses available for sale divided by number of sales for the month the property went on the market)	5.86	0.73	6.06	0.92	– 7.45
Vacant (1 = Yes; 0 = No)	0.11	0.31	0.11	0.31	– 0.09
Winter (percentage of marketing time in)	0.24	0.37	0.23	0.30	1.67
Spring (percentage of marketing time in)	0.30	0.40	0.26	0.31	3.94
Summer (percentage of marketing time in)	0.27	0.38	0.28	0.32	– 0.62
Fall (percentage of marketing time in)	0.18	0.32	0.24	0.31	– 5.47
Sighat	0.06	0.01	0.06	0.02	– 5.47
Sighat DOP*	– 0.00	0.01	0.00	0.01	– 7.05
t (duration)	58.03	51.67	110.41	67.86	– 25.91
DOP	– 0.01	0.15	0.02	0.13	– 7.30

(1860 square feet versus 2000 square feet) than houses which were offered for sale and subsequently withdrawn.

Market conditions during the study period suggest a robust housing market. Mortgage rates were decreasing: the FHA 30-year rate was at 8.58 percent in September 1996, a high for the year, decreasing to 7.51 percent by the end of 1997. Also, approximately 5.5 months of inventory was available for sale each month, with inventory calculated as the total listings in a month divided by the average number of sales per month over the last year. The Texas A&M Real Estate Center 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, the time-until-sale was relatively low at 58 days. The average TOM for properties that did not sell was 110 days.

Some 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. Other property-related variables include the size of the property (*Square Feet*), the age of the house, and binary variables indicating the lack of a garage, the presence of a pool and the presence of one or more fireplaces. Another variable accounts for the number of stories in the house. Several geographic variables, specifying areas defined by the MLS, are included to account for locational variation. Finally, the variable, *Vacant*, is included to account for houses that are unoccupied while they are on the market. Zuehlke (1987), among others, emphasize the importance of including a vacancy measure in these types of models. Finally, several cross-effects are included to account for non-linearities.

The variables, *Spring*, *Summer*, and *Fall*, account for seasonal variations in marketing time. In practice, a house may be offered during more than one season. Therefore, these variables are defined to represent the fraction of the marketing period occurring in a particular season. *Spring* includes 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 construct may bias the empirical estimates downward because the fraction of the marketing time spent in a season with a higher sales rate tends to be lower.

Some variables are included to control for market conditions.[10] 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.[11]

The variables used to explain the list price and TOM are coded 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. *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 $\textit{Time-Off} - \textit{Time Listed} = 1$. Specifically, in Table 2, the suffix *On* indicates the data is based on the listing month. The absence of a suffix indicates either that an average is being used or that the variable is constant over time.

Finally, for each house, *Sighat* is the estimated weight used to correct for heteroscedasticity in the list price equation.[12] This variable also identifies the types of houses with an unusually high or low variance of list price, presumably due to omitted variables that are correlated with other characteristics of a house.

Table 2. Determinants of list price (using the heteroscedasticity correction; the dependent variable is log(list price)).

Variable	Coefficient	*t*-Statistic
Constant	10.90	28.22
Square Feet	0.73	23.43
Square Feet – SQ	– 0.10	– 12.84
Age	– 0.13	– 9.77
Age – SQ	0.02	9.24
2 Bedroom	– 0.03	– 1.33
4 Bedroom	0.05	1.87
5 Bedroom	0.09	1.29
1 Bath	– 0.01	– 0.15
1.5 Bath	– 0.02	– 0.81
2.5 Bath	0.00	0.08
3 Bath	– 0.03	– 0.48
3.5 Bath	– 0.07	– 0.87
4 Bath	– 0.22	– 1.73
Pool	0.09	15.19
Fireplace	0.02	2.06
Stories	– 0.13	– 10.12
No Garage	0.14	4.04
Vacant	– 0.01	– 2.08
MLS Area 82	0.11	13.06
MLS Area 83	0.05	5.19
MLS Area 84	– 0.14	– 9.06
MLS Area 86	– 0.15	– 15.73
MLS Area 87	0.01	0.99
MLS Area 88	– 0.09	– 10.96
Square Feet x Baths	0.09	5.03
Square Feet x No garage	– 0.05	– 4.15
Bedrooms x Bathrooms	– 0.03	– 2.10
Square Feet x Age	– 0.04	– 7.89
Age x Stories	0.05	7.40
Age x No Garage	– 0.04	6.02
Time-Listed	0.00	– 0.15
Inventory-On	– 0.01	– 0.71
Sales-On	0.02	3.10
Rate-On	– 0.03	– 0.61
Spring-On	0.00	– 0.05
Summer-On	– 0.02	– 1.23
Fall-On	0.00	– 0.03
# Observations	3,685	
R^2	0.88	

5. Results

The results for the list price model (Table 2) are similar to the results of other studies. Most 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, the results suggest list prices do not vary by season. Of the market-oriented variables, only *Sales* was significant. The result for *Sales*, a measure of demand, suggests that list prices increase with increasing sales volume, implying that sellers compensate for the price uncertainty associated with increased market activity by raising their prices. However, the coefficient on *Inventory*, a measure of housing supply, is insignificant, suggesting that sellers are patient and do not drop their prices in response to increased competition. Also, the cost of financing, as measured by *Rate*, does not have a significant impact on the list price. Typical for studies of this type, *Vacancy* shows a significant and negative coefficient, however, the magnitude of the estimate suggests a small impact on the list price. Physical and locational characteristics seem to dominate as the determinants of the list price.

The main purpose of the list price model is to create *DOP*. For this data set, the mean value of *DOP* for houses that sold is -0.0145 (i.e., *ceteris paribus*, the list price of such houses is 1.45 percent less than the average). For houses which are withdrawn, the mean is 0.0183, or 1.83 percent above the average. This difference in means results in a test statistic of 8.1 which is significant at beyond the 0.01 percent level. The standard deviation of *DOP* for each sample (sold or withdrawn) is much larger than the difference between the means. We presume that variation within a sample is primarily due to omitted variables. The difference between the samples should be due to differences in the bargaining power, as demonstrated by the willingness to withdraw. A similar but smaller difference exists between samples for houses which were sold quickly and those that lingered on the market.

Analysis shows that the Kaplan–Meier estimates of the hazard rates, not conditioned on explanatory variables, vary with duration. The hazard rate of sale, which is the probability of the house being sold during a given week, is roughly constant at about 5 percent. At the same time, the per-week probability that a seller withdraws rises with duration. Spikes in the hazard rate of withdrawals occur at three, four and especially six months after the listing agreement is signed. The spikes are not easily explained. Even though they occur near month ends, 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 about 156 days. This average holds true for both sold and withdrawn listings.

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 TOM. 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.

The left hand pair of columns (Table 3) show the results for our preferred specification. In support of the theory, the coefficients on *DOP* are significant and show that an increase in the list price above the expected list price increases the expected TOM. Overall, at $DOP = 0$, a one percent increase in the list price increases the average TOM by 1.7 percent. The negative and significant coefficient on the cross-effect, *Sighat***DOP*, reveals that houses in a market segment with a low variance of list price are more sensitive to deviations from the expected list price. That is, given a group of homogenous houses with a narrow range of list prices, a seller who lists his house above the others can expect a much longer marketing period than if the group of houses had more divergent list prices.

Table 3. Determinants of time-on-the-market (TOM).

	Weibull Hazard Model		Log-Linear OLS		Weibull Hazard Model (Ignoring Censoring)	
Variable	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
Constant	39.90	5.65	13.663	2.15	26.75	3.71
Square Feet	0.39	5.04	0.23	3.19	0.17	2.63
Age	− 0.11	− 2.88	− 0.09	− 2.59	− 0.03	− 1.18
2 Bedroom	− 0.27	− 1.58	0.01	0.08	− 0.16	− 1.35
4 Bedroom	− 0.09	− 1.31	− 0.08	− 1.31	− 0.07	− 1.23
5 Bedroom	− 0.44	− 2.38	− 0.17	− 1.04	− 0.07	− 0.44
1 Bath	0.25	1.69	0.07	0.53	0.21	2.05
1.5 Bath	− 0.26	− 1.58	− 0.07	− 0.47	− 0.12	− 1.01
2.5 Bath	0.05	0.63	0.06	0.78	0.08	1.07
3 Bath	0.08	0.74	0.11	1.16	0.14	1.47
3.5 Bath	0.17	1.01	0.16	0.97	0.14	0.96
4 Bath	0.13	0.43	0.25	0.94	0.04	0.10
Pool	− 0.19	− 2.82	0.00	0.06	0.01	0.11
Fireplace	− 0.06	− 0.63	− 0.18	− 2.07	− 0.09	− 1.32
Stories	0.27	3.56	0.13	1.74	0.01	0.23
No Garage	1.08	8.16	0.11	0.79	0.09	0.75
Vacant	0.13	1.74	0.14	2.04	0.12	2.00
MLS Area 82	− 0.29	− 3.32	− 0.09	− 1.12	− 0.17	− 2.44
MLS Area 83	− 0.34	− 3.44	− 0.24	− 2.68	− 0.24	− 3.50
MLS Area 84	− 0.12	− 0.80	0.09	0.67	− 0.11	− 0.94
MLS Area 86	− 0.10	− 1.06	0.04	0.42	− 0.02	− 0.33
MLS Area 87	0.20	2.90	0.11	1.64	0.04	0.73
MLS Area 88	0.20	2.53	0.18	2.32	0.08	1.26
Spring-On	0.20	1.22	− 0.11	− 0.74	0.01	0.05
Summer-On	− 0.61	− 2.82	− 0.31	− 1.56	− 0.54	− 2.49
Fall-On	− 0.88	− 3.83	− 0.36	− 1.76	− 0.82	− 3.53
Inventory-On	1.21	8.92	0.69	5.63	0.94	6.85
Sales-On	0.24	2.25	0.07	0.69	0.16	1.45
Rate-On	− 5.42	− 5.56	− 1.77	− 2.02	− 3.53	− 3.54
DOP	3.03	4.05	1.66	2.27	1.53	2.44
DOP^2	1.63	1.70	− 2.02	− 2.06	0.36	0.49
*Sighat*DOP*	− 23.48	− 2.16	− 25.15	− 2.30	− 22.85	− 2.37
θ	1.01	6.74				
φ	0.73	25.48			0.78	51.83
# Observations	3,685		2,022		2,022	
Log-likelihood	− 4,413.9				− 2,665.2	
Log-$L(\beta = 0)$	− 5178.4				− 2,869.6	
R^2			0.13			

Analysis shows that houses in the sample having a low variance of list prices tend to be smaller and newer than the average house.

The results for the TOM model visibly demonstrate the impact of market conditions. 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. Thus, while the supply of real estate does not seem to affect the list price, it does seem to have a very conspicuous impact on TOM. The demand measure, *Sales*, also suggests an increase in TOM (albeit slight) as demand increases. As a surprise to few, *Winter* is the season with the highest expected TOM. It may surprise some readers that no significant difference in TOM exists between *Winter* and *Spring*, although there is a difference between those seasons and *Summer* and *Fall*. The estimated coefficient for duration dependence, φ, 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] This result is similar to that of Zuehlke (1987).

A central focus of this paper is the method of analysing the determinants of TOM and the impact of houses that were withdrawn from the market. To better understand our results, we compared our methodology to two other commonly used methods. These results are shown in last two pairs of columns of Table 3. The middle pair of columns report the results for a simpler econometric model without consideration of the houses withdrawn from the market: estimation using OLS[14] with $\log(t)$ as the dependent variable and using only the data on houses that were sold. The last two columns again use only the data on sold houses and report on the estimates derived from a Weibull hazard model with heterogeneity correction but without a correction for censoring.

Comparing our preferred specification to the OLS specification, we find fewer significant coefficients in the OLS model. The lower levels of statistical significance are consistent with the expectations for an inefficient estimation methodology. Most of the coefficient estimates of the different models are roughly consistent in terms of magnitudes and direction. An exception is the coefficient on DOP^2 which is opposite in sign and is significant in the OLS model. The coefficient on *Vacant* is significant at the 5 percent level in the OLS model. Compared to our preferred model, the absolute values of the coefficients for *Rate*, *Inventory*, and *DOP* are substantially reduced in magnitude in the OLS estimation, while those on *Sales* and two of the season variables become insignificant.

The second specification shows differences that might become apparent when using an improved methodology, while still ignoring the impact of censoring due to houses being withdrawn. These estimates find no evidence of unmeasured heterogeneity whereas those shown in left hand columns indicate that heterogeneity is a significant feature. The Weibull model results, using only the sold houses, shows that the absolute value of all of the market condition coefficients increases when the methodology recognizes censoring. Also, eight coefficients that are significant in the preferred specification become insignificant when the model is estimated without the withdrawn houses. Therefore, we conclude that the choice of econometric methodology and the quality of the data affect the conclusions drawn from TOM models in ways that are both statistically and economically important.

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.

The selling price discount, calculated as $[1 - p^S/p^L]$, is often used by practitioners as an

Table 4. The determinants of selling price (using the heteroscedasticity correction; the dependent variable is log(selling price)).

Variable	Coefficient	*t*-Statistic
Constant	10.65	105.38
Square Feet	0.72	17.55
Square Feet – SQ	– 0.11	– 9.19
Age	– 0.09	– 4.78
Age – SQ	0.01	5.39
2 Bedroom	– 0.12	– 3.91
4 Bedroom	0.10	2.99
5 Bedroom	0.18	2.14
1 Bath	– 0.02	– 0.49
1.5 Bath	– 0.03	– 0.92
2.5 Bath	0.03	0.82
3 Bath	0.01	0.20
3.5 Bath	– 0.05	– 0.44
4 Bath	– 0.14	– 0.87
Pool	0.11	14.09
Fireplace	0.02	1.55
Stories	– 0.12	– 6.71
No Garage	0.16	1.80
Vacant	– 0.02	– 2.82
MLS Area 82	0.12	12.21
MLS Area 83	0.07	6.42
MLS Area 84	– 0.14	– 7.97
MLS Area 86	– 0.13	– 10.89
MLS Area 87	0.01	0.71
MLS Area 88	– 0.08	– 7.29
Square Feet x Baths	0.11	4.53
Square Feet x No garage	– 0.11	– 3.13
Bedrooms x Bathrooms	– 0.05	– 3.05
Square Feet x Age	– 0.05	– 7.33
Age x Stories	0.03	3.73
Age x No Garage	– 0.03	– 2.07
Time-Off	0.00	0.44
# Observations	2,022	
R^2	0.89	

indicator of changing market conditions. 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 a trivial amount of explanatory power ($R^2 = 0.0035$). We offer no particular predictions about this relationship. However, it is difficult to imagine the existence of any predictability. If, for example, a 1 percent increase in the list price leads to an average 1 percent increase in the selling price, then the only source of variation in the discount would be random (i.e., the identity of the buyer). This example is not entirely unreasonable since the cost associated with a tougher bargaining strategy appears as an independent dimension: TOM. An increase in the expected time required to sell 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 selling price, and the TOM. The theoretical model shows that one should recognize that there is no direct trade-off between the selling price and TOM but that market conditions generate a locus which describes how the expected selling price and the expected TOM vary jointly based on the choice of the list price. The empirical analysis uses a two stage process to estimate a 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 TOM and selling price.

We find that increases in the list price increase TOM and that the effect is magnified for those types of houses with a low variance of list prices. Thus, a seller in a market segment with little variation in list prices, holding quality constant, imposes extra penalties on himself for choosing a high list price. An increase in market inventory lengthens TOM for an individual seller. We also demonstrate that the results from models of this type depend significantly on the choice of methodology and on the quality of the data, namely whether the data includes data on houses that do not sell and the model accounts for censoring.

Our model predicts a relationship between the list 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. We find 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 selling 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, that is, 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. Second, our analysis shows that censoring of the sale process by withdrawals affects the estimates. 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 or are sold by the owner.

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Notes

1. The locus is essentially a set of potential expected selling price and expected TOM combinations. Trippi (1977) presents a similar approach and, using estimates derived from his data, he shows how changes in the type of house can change the locus. The concept of the price-TOM locus is parallel to the concept of the efficient frontier, with the price-TOM combinations occurring on the upward-sloping frontier being the relevant trade-offs. That is, the relevant portion of the locus is either the shortest DOM for a given price or the highest price for a given DOM. Arnold's (1999) model proposes that a seller has two decision variables: the list price and the reservation price. For this case, the locus would be 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).
2. Knight (2002) reports that 37.5 percent of houses recorded a price change. 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. Anglin (1994) reports 46 percent in a smaller data set. Ortola-Magne and Merlo (2000) report that about one-quarter of sellers changed their list price before sale. They also note that changes in list price can be large: in their words, the change in list price is ''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, we focus on other issues. Unobserved changes in the list price may affect the estimate of φ in Table 3 since it captures duration dependent effects.
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 σ^2 and the variance of b is s^2, then the correlation between $(a-b)$ and $(a+b)$ is $(\sigma^2-s^2)/(\sigma^2+s^2)$. In principle, this correlation could be positive or negative but if σ^2 is much larger than s^2, then the intuitively appealing case emerges. Knight et al. (1994) present a more complete model of buyer behavior.
4. Although, recently sellers in the United States (circa. 2000) have been observed setting lower prices on their houses and letting competing bidders drive the price upward from the list 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 exceeding the list price. In Knight (2002), about 14 percent of houses sold at a price in excess of the list price.
6. We tried several alternative specifications of the baseline hazard function. The results of all specifications are similar.
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 size (square footage). To avoid estimating separate equations based on an arbitrary segmentation of the market (as done by some other authors), the 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. The final data set had 3,874 observations.
9. This fraction is relatively robust over time and, using a different data set, is confirmed for another city.
10. Comments by a referee raised the concern that, given the relatively short time period, the indicators of market conditions may be correlated. An OLS regression of *Sales* on a constant, *Inventory* and *Rate* produces an R^2 of less than 0.2.
11. 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.

12. We assume that heteroscedasticity in the list price equation would be described by an exponential function. Using the residuals to an OLS regression, *e*, we identify the characteristics of a house that are 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 $\log(p^{\mathrm{L}})$ using GLS.
13. The estimate φ should be interpreted carefully since it may combine the effects of ordinary duration dependence in the sale process, such as stigma, and the effects of time-dependent decreases in the list price, as documented by Knight (2002) and Ortola-Magne and Merlo (2000). Resolving this problem is a matter of on-going research.
14. Note that we do not need to use two-stage least squares (2SLS) to eliminate any simultaneity bias because we do not use any information on the sale price to explain TOM.

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