

# Mispricing and Optimal Time on the Market

Paul K. Asabere\*  
Forrest E. Huffman\*  
Seyed Mehdian\*

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**Abstract.** This study is an empirical examination of the relationship between pricing and optimal time on the market (*TOM*). First, estimates of optimal *TOMs* for our data set are generated using a linear programming model. Next, a workable measure of pricing is provided based on predicted listing prices and predicted sales prices. We are then able to measure directly the relationship between pricing and optimal *TOM*. The results of our analysis indicate that both overpricing and underpricing would prevent the achievement of optimal *TOM* and result in suboptimal sales prices.

Real estate sellers face the trade-off between two conflicting requirements: the desire to maximize selling price while minimizing time on the market (Miller, 1978; Trippi, 1977). The key variable in resolving this quandary is the determination of the "optimal" listing price for the property up for sale. Optimal listing prices maximize the present value of the net selling price given the seller's opportunity costs (Miller and Sklarz, 1987).

Low listing prices reduce the likelihood of receiving prices close to market values.<sup>1</sup> Although marketing time might decrease as a result of low listing prices, the net present value of the sale may not necessarily be maximized. On the other hand, high listing prices may discourage bids relative to true market values. Thus, high listing prices could result in lengthy time on the market due to the rejection of supposedly unacceptable offers. Of greatest concern is the standard practice of overpricing in hopes of receiving all possible bids (Miller, 1978). A recent study by Asabere and Huffman (1993) discovers that overpricing leads to suboptimal values in a buyers' market.

Since true market values are difficult to ascertain in relatively inefficient real estate markets, the presence and effect of overpricing have been measured indirectly by examining the relationship of sales prices and time on the market (*TOM*), with increased *TOM* serving as evidence of overpricing and lower *TOM* signalling underpricing. Attempts to examine such pricing decisions are fairly recent, with the earliest studies occurring in the mid-1970s (see Asabere and Huffman, 1993; Belkin et al., 1976; Cubbins, 1974; Geltner et al., 1991; Haurin, 1988; Miller, 1978). Unfortunately, the resulting empirical evidence on the relationship between sales price and time on the market (*TOM*) has been mixed and somewhat inconclusive. Specifically, the sign on *TOM* has been found to be rather unpredictable. Trippi (1977), Miller (1978), and Asabere and Huffman (1993) find a positive relationship between price and *TOM*. However, Cubbins (1974) finds an inverse relationship. Belkin et al. (1976) find that the ratio of selling price to list price is negatively related to *TOM*.

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\*School of Business and Management, Temple University, Philadelphia, Pennsylvania 19122.  
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Our study contributes to the existing empirical literature in two ways. First, estimates of optimal *TOMs* for our data set of single-family home sales are generated using a linear programming model. Next, a workable measure of mispricing is provided that defines actual mispricing as the difference between “brokerage value” (that is, the value in the mind of the seller based on the distribution of listing prices of comparable properties in the market) and “market value,” which is based on actual sales prices of comparable properties (explained in the third section of this article). We are then able to measure directly the relationship between mispricing and optimal *TOM*. Our results indicate that both overpricing and underpricing would prevent sellers from achieving optimal *TOM*.

The rest of the study is organized as follows: the second section presents our model for deriving optimal *TOM* and section three presents our model of the relationships between mispricing and optimal *TOM*. Section four then presents our summary and implications.

### Estimating Optimal *TOM*

The underlying assumption of our model for deriving optimal *TOM* is that the seller has the dual objective of minimizing *TOM* while maximizing sales price.<sup>2</sup> Hence, one can formulate an objective function in which *TOM* is minimized subject to a set of constraints imposed by property characteristics and market conditions.

Consequently, we utilize a linear programming model that calculates optimal *TOM* as a linear combination of all properties in the data set given the constraints derived from property and market characteristics. Specifically, the following linear programming model is solved for each sales observation to obtain optimal *TOM* for that observation given the inclusion of all other properties in the sample. Thus,

$$\text{Min}TOM = \sum_{i=1}^K TOM_i X_i \quad (1)$$

where  $i = 1 \dots K$  subject to

$$\begin{aligned} \mathbf{r}_i &\geq \mathbf{X}\mathbf{r} \\ \mathbf{X}\mathbf{S} &\geq \mathbf{S}_i \\ \mathbf{X} &\geq 0, \end{aligned}$$

where

- $\mathbf{r}$  = vector of variables whose lower values are preferable (specifically, mortgage loan rates);
- $\mathbf{S}$  = vector of variables whose higher values are preferable (specifically, sales price);
- $\mathbf{X}$  = decision variables;
- TOM* = actual number of days on the market;
- $K$  = number of properties in the sample.

This program is solved for each observation ( $i = 1, \dots, K$ ) to determine the least numbers of days on the market that will satisfy all constraints. The program thus computes the

optimal (minimum) *TOM* for each property in the sample. The first set of constraints are for variables (*r*'s) whose lower values would minimize *TOM*. In this instance we use mortgage interest rates as a proxy for all such influences. The left-hand side variable is the observed value of *r* for the property *i*. The right-hand side of the inequality serves as the theoretically lowest value of *r*. The X-vector (decision, or intensity vector) contains weights given by the linear program. In the case of equality, the *r<sub>i</sub>* is equal to the theoretically lowest value of *r*.

The second set of constraints (*S*'s) are for variables whose higher values are preferable. The left-hand side represents the theoretically highest value of *S* which is calculated as the weighted sum of all properties in the sample (where the weights, X-vector, are assigned to each property by linear programming problem). The right-hand side of this constraint is the observed value of *S* for property *i*. The observed value of *S* for property *i* is compared to this theoretically highest value while *TOM* is minimized. If equality holds, *S<sub>i</sub>* is the theoretically highest value of variable *S*.

In sum, the results of the objective function are the optimal *TOM*/sales price combinations achievable within our data set.<sup>3</sup> Deviations from optimal *TOM* (either positive or negative) would be suboptimal by definition. We estimate our objective function by using home sales data from the Philadelphia area.

Our data consist of 337 sales of residential real estate from December 1986 to June 1990. The data were obtained from three multiple listing services covering the City of Philadelphia and two outlying suburban and rural areas, Montgomery and Chester counties. The distribution of the 337 sales is as follows: 125 sales are from the city of Philadelphia (urban); 100 sales are from Montgomery county (suburban); and 112 sales are from Chester county (rural). The MLS data contain information on actual sales price, listing price, time on the market (*TOM*), conventional property characteristics and time of sale. Neighborhood (census tract) variables and a financing variable (rate of interest on a conventional mortgage) are added.

Exhibit 1 presents summary statistics for the key variables—actual and optimal *TOM* for the combined data, as well as the segments of data for urban, suburban and rural. As shown in Exhibit 1, urban homes remained on the market an average of 147 days. The corresponding figures for suburban and rural homes are 129 days and 97 days, respectively. The mean optimal *TOM* for urban homes is 57 days. The corresponding figures for suburban and rural are 44 days and 33 days, respectively. A parametric means test of the differences between actual and optimal *TOM*s for urban, suburban, and rural is performed, using the ANOVA technique. The calculated *F*-values for differences

**Exhibit 1**  
**Summary Statistics of Key Variables**

	All		Urban		Suburban		Rural	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Actual <i>TOM</i>	125.4	81.6	146.8	76.1	129.4	70.1	96.8	89.3
Optimal <i>TOM</i>	45.3	45.6	57.1	29.4	44.2	53.8	33.3	49.3
$\hat{P}_L$	\$193,562	\$117,799	\$172,882	\$94,869	\$210,850	\$120,446	\$201,207	\$118,456
$\hat{P}_S$	\$191,441	\$102,296	\$157,450	\$87,023	\$199,536	\$109,370	\$192,061	\$107,193
$(\hat{P}_L - \hat{P}_S)$	\$12,121	\$10,654	\$15,433	\$8,393	\$11,313	\$11,276	\$9,145	\$11,385

between the means of actual and optimal *TOMs* for urban, suburban, and rural properties are significant at the 1% probability level. While these differences between urban, suburban, and rural may be peculiar to our study area, they can be explained by city policies that have made the city less attractive (higher property taxes, wage taxes, and higher property transfer taxes) versus suburban and rural areas. These disadvantages, in addition to the presence of other suburban and rural amenities such as better school districts, less traffic and reduced crime, may help explain differences in *TOMs*.

## The Model and the Empirical Results

Our hypothesis is that deviations from optimal *TOM* are the result of mispricing. In our model, deviations from optimal *TOM* should either be a random event or be explained by mispricing. In this model, listing prices are a function of the distribution of listing prices of comparable properties in the market. This brokerage value could be modelled as a predicted listing price based on a standard hedonic model of list prices.<sup>4</sup> As noted earlier, we distinguish between brokerage value and market value, which is modelled as the predicted sales price based on a standard hedonic model of actual sales prices. We then define “mispricing” as the difference between brokerage value and market value. In general, we expect a strong relationship between mispricing and optimal *TOM*. Equation 2 is used to capture our related hypotheses.

$$\text{Log}(\text{min}TOM) = \text{Log}\beta_0 + \beta_1\text{Log}(\hat{P}_L - \hat{P}_S) + \varepsilon, \quad (2)$$

where:

*minTOM* = our variable for optimal *TOM* defined in section two.

$\hat{P}_L$  = predicted listing price of the *i*th house (brokerage value) derived by a standard hedonic equation of list prices and conventional physical property characteristics, location, neighborhood, macro variables, time of sales and an error term.<sup>5</sup>

$\hat{P}_S$  = predicted sales price of the *i*th house (market value) derived by a standard hedonic equation of actual sales prices and conventional physical property characteristics, location, neighborhood, macro variables, time of sale and an error term.

$(\hat{P}_L - \hat{P}_S)$  = denotes potential mispricing. Of course,  $(\hat{P}_L - \hat{P}_S > 0)$  denotes potential overpricing while  $(\hat{P}_L - \hat{P}_S < 0)$  denotes potential underpricing. The mean value for mispricing for our combined data is \$12,121. The minimum and maximum values are \$-7,428 and \$69,972, respectively.

$\varepsilon$  = a random error term.

Of particular importance are the signs on the overpricing ( $\hat{P}_L - \hat{P}_S > 0$ ) and underpricing ( $\hat{P}_L - \hat{P}_S < 0$ ) variables. When overpricing is the case, we expect a positive relationship between overpricing and optimal *TOM*. For underpricing we expect an inverse relationship between underpricing and optimal *TOM*. It must be noted, however, that all deviations from optimal *TOM* (negative or positive) are suboptimal by

## Exhibit 2 Regression Results

$$[\text{Log}(\min TOM) = \text{Log}\beta_0 + \beta_1 \text{Log}(\hat{P}_L - \hat{P}_S) + \varepsilon]$$

	Overpricing			Underpricing
	All Obs.	Suburban	Rural	All Obs.
Intercept	-.31 (-0.67)	1.34 (2.3)*	-3.06 (-3.0)*	6.69 (6.1)*
Coefficient	.41 (8.1)*	.23 (3.6)*	.65 (5.7)*	-.50 (-3.5)*
$R^2$	.18	.13	.26	.30
F-Value	65.7*	12.7*	32.3*	12.2*
N	306	100	112	31

*Notes:*

*t*-ratios are shown in parentheses below regression coefficients.

\*denotes significance at the 1% level

No regressions are reported for *URBAN* representing the City of Philadelphia because the estimated coefficient of the mispricing variable is not significant in any of the models.

In the case of underpricing, regressions are not reported for suburban and rural due to insufficient number of observations.

interpretation. More formally, the null hypothesis is that  $\beta_1$  in equation 2 would be equal to zero ( $H_0: \beta_1 = 0$ ). The alternative hypothesis is that  $\beta_1$  would be significantly different from zero ( $H_1: \beta_1 \neq 0$ ).

Our test results using the data described in section two are summarized in Exhibit 2. Three functional forms were initially tested: standard linear form, semi-logarithmic form, and the double-logarithmic form. The double-logarithmic form (equation 2) is provided for discussion because of our preferred interpretation of the coefficient in terms of elasticities. The other forms of equations yielded qualitatively similar results. Because the methodology of this study is applied to cross-sectional data, there exists the potential for heteroscedasticity. The Glejser (1964) test for heteroscedasticity was unable to reject homoscedasticity in any of the underlying models. Therefore, the models are taken to be well specified. Analyses of the correlation matrix of relevant variables also indicated no serious problems of collinearity. In fact, the correlation coefficients of relevant variables are less than .50 in all cases.

The explanatory power ( $R^2$ ) of the four reported equations range from .13 to .30. These adjusted  $R^2$ s seem reasonably good given prior research results and the exploratory nature of this study. The low  $R^2$ s, however, indicate that there are probably reasons other than mispricing that account for deviations from optimal *TOM*. For instance, it may be useful to consider specific real estate agent characteristics. For instance, greater agent "efficiency" would affect optimum *TOM*. Lack of data, however, prevents us from including variables that control for such influences. Also, it must be noted that, at this point, our goal is a relatively simple one of trying to quantify the basic relationships between mispricing and optimal *TOM*, as opposed to providing an empirical model that completely explains variations in *TOM*.

The alternative hypothesis (i.e.,  $\beta_1 \neq 0$ ) is confirmed by our results. The estimated coefficient of the overpricing ( $\hat{P}_L - \hat{P}_S > 0$ ) variable is significantly positive in the three reported equations at the 1% level. The magnitudes of the estimated coefficient range from .23 to .65. Based on the combined data, for example, overpricing by 1% produces an excess of .41% beyond optimal *TOM*. The corresponding figures for suburban and rural are .23% and .65% respectively. The estimated coefficient of the underpricing ( $\hat{P}_L - \hat{P}_S < 0$ ) variable is significantly negative at the 1% level. The magnitude of the estimated coefficient of the underpricing variable is  $-.50$ , meaning that underpricing by 1% results in a .50% (half of a percent) shortfall below optimal *TOM*.

## Summary and Implications

The hypotheses of this study are borne out by our results. The estimated coefficient of the overpricing and underpricing variables are significantly positive and negative, respectively at the 1% level. The results indicate that both overpricing and underpricing would prevent the achievement of optimal *TOM*. The evidence is consistent with theory that there exists a trade-off between listing pricing and time on the market. In particular, the normative implication of this study is that the common strategy of overpricing in the hopes of receiving all possible bids would be suboptimal and counterproductive.

This research is exploratory in nature. The significant results suggest a need for further research on the relationships between mispricing and time on the market. Additional avenues of research include: models that incorporate variables that control for broker and seller characteristics (not included here due to lack of data); and comprehensive models that attempt to unearth all the major determinants of time on the market.

## Notes

<sup>1</sup>Assuming that bids are received in sequence, with bids close or equal to the listed price accepted as offered, a tenable assumption in real estate markets where the distribution of bids is unknown.

<sup>2</sup>However, there may be a possible conflict between the objective functions of the seller and the real estate agent. As noted by a reviewer, real estate agents, with differing opportunity costs, in the short term, prefer the faster turnover associated with low listing prices. However, a pattern of low sales prices relative to comparable properties would ultimately result in general seller dissatisfaction and lower broker revenues from loss of business. By moving his inventory faster and at maximum prices, the agent offers the highest quality of service to his clients over the long term. In addition, the real estate agent violates the best interests of his principal (the seller) at his/her legal peril. Therefore, it seems reasonable to assume that the proposition maintained here is not unduly compromised by the possibility of real estate agent misadventure. For studies that address the issue of potential agency problems in this context see (Geltner, 1991; Miceli, 1989; Miller and Sklarz, 1987).

<sup>3</sup>As also noted by an anonymous reviewer, optimal *TOM* may be influenced by variables other than sales price and mortgage rates. For instance, it appears that expansionary periods would reduce *TOM* while contractionary periods would increase *TOM*. Our study period December 1986 to June 1990 is a period of decline (a buyer's market) for the study area as described by Asabere and Huffman (1993). Thus, there is no need to control for periods of expansion or contraction.

*TOM* may also be influenced by supply factors such as the quantity of like-type dwellings available for sale at any given point in time, and on the demand side, it may be useful to consider the number of prospective buyers. While these supply and demand variables were not included in equation 1 for modeling optimal *TOM* (due to lack of data), they enter indirectly into the right-hand side of equation 2 for explaining optimal *TOM*. The predicted list prices and predicted sales prices in equation 2 are based on hedonic functions. The hedonic pricing equations used conventional variables that represent both the demand and supply sides of the market (see Note 4).

<sup>4</sup>The hedonic equations for list prices ( $\hat{P}_L$ ) and sales prices ( $\hat{P}_S$ ) are both estimated using several conventional explanatory variables. Specifically, the following variables are considered in the hedonic regressions: lot size, bedrooms, bathrooms, building condition, median income of neighborhood, median rent of neighborhood, proportion of homes abandoned, urban, suburban, and rural locations (as applicable), time of sale (with different specifications for time, including a continuous month-of-sale variable, dummy variables for seasons, and other specification forms for seasonality), unemployment rate, and the rate on a thirty-year conventional mortgage. Significant variables for our data are: lot size, bedrooms, bathrooms, median rent, urban, suburban, time of sale, and mortgage rate. These variables are included in the final regressions used to predict list prices ( $P_L$ ) and sales prices ( $P_S$ ). These variables are representatives of regressors used in other studies and there is no need to say much about them.

<sup>5</sup>Another issue raised by an anonymous reviewer is the potential problem of omitted variables in the underlying hedonic pricing equations and their effect on model 2. Granted that there may be omitted variables as with other hedonic studies, we expect any impacts due to omitted variables to be systematic between  $\hat{P}_L$  and  $\hat{P}_S$  since we have no reason to suspect that the attribute elasticities with respect to omitted variables would be different for the two pricing regimes, ( $\hat{P}_L$  and  $\hat{P}_S$ ). Any impacts due to omitted variables would be imbedded equally in the intercept terms of the two pricing regimes and thus would not affect model 2 in any major way.

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