Pricing in an illiquid real estate market

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Abstract

Using a repeat sales data set, this paper tests whether a single small seller can influence the selling price of their house. We find that this influence exists and that it dominates the influence of commonly-used market conditions. Since the estimated magnitude of the effect is larger than expected, we verify the estimate using several supplementary tests.

JEL: C78, D80, R21, R31
Key Words: liquidity, search, matching, bargaining, time-till-sale, market frictions, real estate, selling price, list price, competition

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Analyses of real estate markets suffer from a kind of split personality. Many analyses use the perfectly competitive model because it provides powerful insights. At the same time, many features of real estate market, such as bargaining and highly-paid brokers, seem to exist because this market does not fulfill the textbook ideals of perfect information and price-taking behavior. This kind of tension is the same kind that prompted Arrow (1959) to argue that:

“there exists a logical gap in the usual formulations of the theory of the perfectly competitive economy, . . . Each individual participant in the economy is supposed to take prices as given and determine his choices as to purchases and sales accordingly; there is no one whose job it is to make a decision on price” (p. 41, 43)

Economists responded with a collection of coherent responses that became known as Search Theory (e.g. Rothschild, 1973) and evolved into the Random Matching models (e.g. Pissarides, 2000) used by Labour Economists to analyse unemployment and by Real Estate Economists to analyse how long it takes a house to sell. While these analyses focus on the time dimension of the market process, time is a significant variable because time is one aspect of a supposed trade off between time and money. This paper estimates the degree to which a single seller can raise their selling price in a residential real estate market.

It is clear that houses which sell and those which do not sell are priced differently. Several papers1 have estimated the “Degree of Over-Pricing” (DOP) as the percentage difference between the list price offered by a particular seller and the typical list price for that type of house derived from easy-to-observe variables. Using the data set described in Anglin and Wiebe (2002), the mean value of DOP for houses which sold was -0.02 (i.e. ceteris paribus, the list price of such houses was 2 percent less than the estimated typical list price for that type of house) while, for houses which were withdrawn before sale, the mean value was +0.025 or 2.5

percent higher. Figure 1 illustrates this difference by comparing the cumulative distributions of DOP for houses which sold and for those which did not, excepting the minimum and maximum in each set.

A classically trained economist might claim that any finding concerning the list price is unimportant because the market determines the selling price and only the selling price influences variables of real importance. Though he or she might claim that an individual’s real choices are whether to participate in the market or not, footnote 1 lists a large number of papers which link variation in the list price to variation in how long it takes a seller to sell. In response, the classically-trained economist might question whether this aspect of the selling process is as significant as the real magnitudes produced by the process, such as consumption. This paper complements the existing papers by focussing on the link between the variation in DOP to variation in the selling price, i.e. a seller’s wealth.

Economists discussed these sorts of ideas long before Arrow challenged economists to provide a better explanation. Usually, this discussion involved classifying markets according to
their liquidity where the classic definition of liquidity measures the selling price discount necessary to sell quickly, if a seller wanted to sell quickly. Various models have been proposed but they have been rarely applied to a housing market, a famously illiquid market. The fundamental barrier to measuring liquidity in a housing market is that the selling price is influenced by many forces other than bargaining. It is well-known that buyers must engage in a costly search process to evaluate houses. Indirectly, Figure 1 demonstrates the significance of search since the standard deviation of the distributions of the Degree of Over-Pricing is larger than the difference between the distributions: about 0.12 vs. about 0.045. Presumably, the former represents variables omitted from estimation of DOP while, because the difference in the curves represents a difference between sellers who sell and those who do not sell, the latter represents an effect of bargaining.

To limit any effect of omitted variables, this paper uses data on houses that were sold twice and a model which results in a remarkably simple regression equation. We find that a change in DOP by one percentage point is related to a change in the selling price of about one percent, ceteris paribus. We also find that various common indicators of market conditions, such as interest rates and a measure of excess demand, add surprisingly little explanatory power. These findings are confirmed using a variety of indirect approaches, including a test using the same assumptions as a standard hedonic price model. The concluding section offers some thoughts on what our analysis reveals about several classic questions.

Related Literature

The process of selling a house is well-known. A house seller chooses a list price seen by a flow of buyers, some of whom inspect the house and a few may want to buy it. This list price is an instrument used to implement a seller’s desired Degree of Over-Pricing (DOP). Eventually, one buyer bids a high enough price that the seller accepts, or the seller gives up and leaves the active market. Depending on luck, the buyer’s and seller’s bargaining positions and their relative bargaining power, the selling price may be high or low. Since the chosen price influences buyers’ behavior, variation in the DOP generates a locus of possible outcomes, shown in Figure 2.
This story of a trade off between selling price and time-till-sale differs slightly from the story usually told of an illiquid market because the trade off between time and money is not direct. The sequence of events necessary to sell a house implies that a seller cannot lower the selling price directly and that any time spent waiting for a buyer represents a sunk cost during the bargaining phase. In addition, since both the selling price and time-till-sale are random, the relevant trade off is between the expected selling price and the expected time-till-sale. Yavas and Yang (1995) and Arnold (1999) have shown how allowing a more complex strategic relationship between buyer, seller and real estate agent changes little in this Figure. Within the constraints of this “budget set”, a seller’s preferences determine their choice of DOP and, given the type of house, the list price. More generally, if a seller can voluntarily increase the expected time-till-sale then rationality implies that they would do so only if there is an associated benefit. The supposed, but unproven, benefit is an increase in the expected selling price. In a sense, this paper emphasizes the vertical axis in Figure 2 where previous papers have emphasized the horizontal axis.

A few papers have studied bargaining in a real estate market. The first was Turnbull and Sirmans (1993) who argued that buyers who move from one city to another and buyers who have little experience have an observably weak bargaining position; if it were possible to extract
surplus through bargaining, they would be the most likely victims. Turnbull and Sirmans could not reject the hypothesis that bargaining had no effect. Following the best practices of the Scientific Method, Lambson McQueen and Slade (2004) repeated the study with a larger data set. They found a statistically and economically significant effect: out-of-town buyers paid about 5 percent more on an average sale price of more than US$2 million. They offered two hypotheses to explain this effect. First, that buyers coming from high-priced cities would search “too little” in a low price city. Second, that the search process of local buyers is less time constrained. McQueen and Slade found weak support for both of these hypotheses. While most analyses focus on sellers, Londerville (1998) studied how buyers can take advantage of a seller with a weak position.

These papers studied differences in bargaining position while bargaining power is a separate dimension of the bargaining process that is less well-understood. Harding, Sirmans and Rosenthal (2003) used data from the American Housing Survey to identify relative bargaining power. Their ingenious decomposition, combined with a matched data set on buyer seller and housing characteristics, isolated the separate effects of buyer characteristics and of seller characteristics on bargaining power. They found that first time buyers have less bargaining power.

Most studies have focussed on explaining the selling price and time-till-sale because theories which seek to explain the choice of DOP or list price depend on hard-to-measure details. The simplest theories are descriptive; they do not explain why a buyer should attach any importance to any price published before sale because everybody knows that the selling price is determined by negotiations. Behavioral theories based on reference points and discounts may provide the beginnings of an explanation but do not predict a unique market equilibrium. In theories with stronger game-theoretic foundations (Chen and Rosenthal, 1996; Yavas and Yang, 1995), the institution of a list price has a real effect because it is assumed to be an upper bound on the selling price. Unfortunately, this assumption is routinely invalidated even when market conditions are weak. Taylor (1999) used a more sophisticated model of asymmetric information to study the phenomenon of stigma. Using the concept of an Undefeated Perfect Bayesian
Equilibrium to find a separating equilibrium, he showed that the optimal choice of list price depends on the balance between an “option-value” effect and a “signal-damping” effect. The first effect emphasizes the benefits of waiting to sell and the second effect emphasizes the benefits from reducing the information that can be inferred by a buyer if a house has been for-sale for a long time. A formal test of Taylor’s theory would depend on data that are rarely available. Because of these weaknesses and to be consistent with Figure 1, we use a more mechanical approach.

Proposed methodology

When the trade off between time-till-sale and selling price is mediated by the choice of DOP, two steps are needed to estimate the determinants of the selling price. The first step estimates the DOP implied by an announced list price for a house described by X, listed at time LT with market conditions characterized by M:

\[ E(\log(p^l)) = X\alpha^l + M\beta^l + g_1(LT) \]  

(1)

where \( \alpha^l \) and \( \beta^l \) are coefficients to be estimated. \( g_1(\cdot) \) represents the general effects of time, e.g. inflation, and is described more precisely below. When a buyer learns that the list price of a specific house is \( p^l \), they infer that DOP as the deviation:

\[ \text{DOP} = \log(p^l) - E(\log(p^l); X, M, LT) \]

= \( \log(p^l) - (X\alpha^l + M\beta^l + g_1(LT)) \).  

An increase in DOP has been shown to increase expected time-till-sale.  

\(^2\) To estimate the determinants of time-till-sale, many papers (e.g. Yavas and Yang, 1995) use a different regressor, the selling price discount or the ratio of the selling price to the list price, and some use Two-Stage Least Squares to control for simultaneity bias. Implicitly, the second equation in the system of simultaneous equations determines the selling price. Though we estimate the determinants of the selling price, we do not use a measure of time-till-sale as an explanatory variable.

In our opinion, estimating the system of equations, instead of our proposed two step process, has the effect of blending the effects on the variables listed on the two axes in Figure 2. To use a system of demand equations as an analogy, one could estimate the quantity demanded of beer using information on the quantity demanded of pizza as an explanatory variable but it would be better to use exogenous variables, such as the prices of beer and pizza. In addition, the footnote 9 in the concluding section notes that knowing the discount may contain less information than expected, especially with our estimate of \( \hat{\delta} \). See Anglin (2003) for more
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Under ideal conditions, DOP could be used as a regressor in a semi-log specification of the selling price equation, such as

\[ E(\log(p^s)) = X \alpha^s + M \beta^s + g_2(ST) + \delta \text{ DOP} \]

(3)

ST represents the time of sale and \( g_2(.) \) represents the effects of inflation and other general trends in prices over time. If a seller cannot influence the price, then \( \delta = 0 \). Unfortunately, variables omitted from the description of a house make it likely that using the residual taken from an equation explaining list price to explain the selling price would produce an absurdly high \( R^2 \) and a misleading estimate of the ability of a seller to set their own price.

To avoid this problem, we use a repeat sales methodology (for an introduction, see DiPasquale and Wheaton’s textbook (1996) or Clapp and Giacotto (1992)) in a way that emphasizes the contribution of the list price. To start, notice that if \( X \) does not change between the first and second sale then equation (3) implies that

\[ E(\log(p_{S2}/p_{S1})) = (M_{S2} - M_{S1}) \beta^s + g_4(ST_{1}, ST_{2}) + \delta (DOP_{2} - DOP_{1}) \]

(4)

and equation (1) implies that

\[ E(\log(p_{L2}/p_{L1})) = (M_{L2} - M_{L1}) \beta^l + g_3(LT_{1}, LT_{2}). \]

(5)

where subscripts 1 and 2 denote the first and second sale of the house. \( g_3(.) \) and \( g_4(.) \) summarize any effect of general inflation. We let DDOP represent the residual generated by equation (5). By construction, DDOP would equal \( (DOP_{2} - DOP_{1}) \) if equation (2) were used to estimate \( DOP_1 \) and \( DOP_2 \) separately. Constructing DDOP in this way also implies that DDOP is orthogonal to the other regressors, including those representing the passage of time. Pagan (1984) argued that using Ordinary Least Squares to estimate a system like equations (4) and (5) would estimate \( (\beta^s, \beta^l, \delta) \) efficiently.

This procedure is consistent with, and easy to implement when using, a semi-log specifications of the price functions. We do not test any conjectures on the signs of \( \beta^s \) or \( \beta^l \) in discussion on this issue.

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3 This equation, together with an equation for the expected time-till-sale, such as \( E(TTS) = F(X, M, DOP) \), could be used to generate the locus in Figure 2 parametrically.
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the price equations. Anglin (2003) showed that the effect on the selling price of a change in market conditions is ambiguous, if viewed as an isolated variable, because a change in market conditions may also alter the trade-off between a quick-sale and a higher price. There exist hypotheses and professional opinions which link selling price, time-till-sale and market conditions but testing them is beyond the scope of this analysis and this data set.

This pair of equations can be simplified further if the purpose is to reject a model of price taking behaviour. Combining equations (2) and (3) directly implies that

\[ E(\log(p^S)) = X(\alpha^S - \delta \alpha^L) + M(\beta^S - \delta \beta^L) + g_2(ST) - \delta g_1(LT) + \delta \log(p^L) \]  

(6)

In an equilibrium model, the only relevant condition on the market price is that quantity supplied equals quantity demanded, which is assumed to be always true. If either the demand curve or supply curve shifts then any indicator of market conditions other than the general level of prices should be irrelevant: thus \( \beta^L = \beta^S = 0 \). If we further assume that the difference between \( LT \) and \( ST \) is irrelevant and if the level of list prices changes at the same rate as the level of selling prices (i.e. \( g_1(.) = g_2(.) \)) then the two stages can be replaced by a single regression:

\[ E(\log(p^S_2/p^S_1)) = (1 - \delta) g_4(ST_1, ST_2) + \delta \log(p^L_2/p^L_1). \]  

(7)

Equation (7) is so simple that it even omits an intercept.

Description of Variables

The data refers to 621 residential houses that were sold during 1999 in Windsor Ontario and at some earlier time with little or no renovation between sales. The data were supplied by the Windsor and Essex County Real Estate Board and is supplemented with data from government statistical bureaus. Houses sold without an agent are not included in the data; professional estimates suggest that this segment is only about 10 percent of the market at any point in time. On average, there was a four year difference between the sales. The earliest sale was 9 years prior. Table 1 summarizes the data used in our study.
Table 1: Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Selling Price #1</td>
<td>112924</td>
<td>41923</td>
</tr>
<tr>
<td>Selling Price #2</td>
<td>118785</td>
<td>43237</td>
</tr>
<tr>
<td>List Price #1</td>
<td>122671</td>
<td>44258</td>
</tr>
<tr>
<td>List Price #2</td>
<td>127898</td>
<td>45880</td>
</tr>
<tr>
<td>Time Difference (in days)</td>
<td>1319</td>
<td>684</td>
</tr>
</tbody>
</table>

Market Conditions during the first sale

FXR (Cdn/US Exchange Rate) | 1.37  | 0.07   |
UR (Local Unemployment Rate) | 9.08  | 1.53   |
SALES (#/Month)              | 424.16| 80.73  |
BALANCE                       | 0.52  | 0.09   |
REAL5 (5-year mortgage interest rate minus inflation rate during the preceding year) | 6.88  | 1.60   |

Generated Regressor

DDOP                           | 0.00  | 0.12   |

We consider three indicators of general economic conditions and two internal indicators of activity in the local housing market. BALANCE is often used as proxy measures of excess demand. BALANCE measures the balance between entry and exit as the ratio of the number of sales to the number of new listings in a month. Our regressions use the difference between the values of these variables on the first and second sale. Our data set is limited in that we do not

As discussed later, information on dates is used to construct slightly different regressors which measure the fraction of each year that a house is owned by the second seller, $\tau_t$. Summary statistics on these regressors are

<table>
<thead>
<tr>
<th>$\tau_t$</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tau_{93}$</td>
<td>0.19</td>
<td>0.67</td>
</tr>
<tr>
<td>$\tau_{94}$</td>
<td>0.22</td>
<td>0.37</td>
</tr>
<tr>
<td>$\tau_{95}$</td>
<td>0.39</td>
<td>0.45</td>
</tr>
<tr>
<td>$\tau_{96}$</td>
<td>0.62</td>
<td>0.44</td>
</tr>
<tr>
<td>$\tau_{97}$</td>
<td>0.80</td>
<td>0.36</td>
</tr>
<tr>
<td>$\tau_{98}$</td>
<td>0.92</td>
<td>0.24</td>
</tr>
<tr>
<td>$\tau_{99}$</td>
<td>0.47</td>
<td>0.26</td>
</tr>
</tbody>
</table>

Including the Canada-US exchange rate in a study of a housing market may seem a bit odd to uninformed readers but, since the Detroit-Windsor border crossing is amongst the busiest border crossings in the world, this measure was suggested by informed real estate professionals.

Some readers may be surprised that the average value is so low. It is consistent with the fact that many houses offered for sale do not sell during the listing period, as documented by Anglin, Rutherford and Springer (2003). Anglin (2004) analysed this phenomenon in greater depth.
have a complete description of each house.

In 1999, the houses sold at an average discount of 4.5 percent from their list price. The selling price exceeded the list price in 2.2 percent of the cases and the selling price was 10 percent or more below the list price in 2.5 percent of cases. For the first sale, the average discount was similar (5.7 percent) but the distribution was more diffuse: 6.7 percent of cases sold for more than list and 9.7 percent of cases sold at a discount of more than 10 percent. Thus, there is little support for a hypothesis claiming that the list price is chosen in direct proportion to a market price that is well-recognized by participants but unknown to the analyst.

At the same time, we should also acknowledge a growing literature which notes that, in practice, the list price is not as fixed as these equations suggest. Knight (2002) and Merlo and Ortalo-Magne (2003) reach roughly the same conclusion: that about 25 to 35 percent of sellers lowered their list price at least once before selling and that the list price fell by about 5 to 8 percent when it did fall. While this phenomenon is well-known, most papers ignore it to focus on other issues for a couple of reasons. The most common reason is that the data on the complete time path of prices are usually not recorded. Second, many theories of a falling prices appeal to Lazear’s (1986) model of optimal learning or to a declining bargaining position (Ben-Shahar, 2002) and, if thought to be relevant, they offer subtle confirmations of the relevance of bargaining. Even in the extreme case of assuming that the list price falls in order to move closer to a (predetermined) market price, then the list price should only affect the time-till-sale and δ is predicted to be zero.

To control for general price trends, we use a flexible functional form. Information on the dates of the first and second sale are used to record the fraction of a year that a house was owned by the first buyer/second seller. More precisely, let

\[ g_4(ST_{1i}, ST_{2i}) = \sum_t \alpha_t \tau_{ti} \]

where \( \tau_{ti} \) is fraction of year \( t \) that the house \( i \) is owned by the second seller and \( \alpha_t \) represents the estimated annual rate of increase during year \( t \). We use a similar expression for \( g_3(.) \) in the other equation. Because of the relatively small sample for the years preceding 1993, we assume that
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the growth rate of prices is constant before 1993.

Clapp and Giacotto (1992, p. 302) and others argue that analysis based on repeat sales data sets may be biassed by the fact that certain types of houses are more likely to be sold twice within a given period of time. The selection of houses into a repeat sales data set, either because one segment of a market is more liquid than others or because resold houses are “lemons”, has ambiguous implications for this study. If a house is a lemon, then signalling activities involving the list price could be important but these activities should not differ systematically between the first and second sales. If selection is caused by a segment of the market being more liquid, then bargaining in that segment may be less significant than for a typical house. On the other hand, the over-represented type of house is the small house bought by somebody as their first house and sold by somebody with more experience. When this difference in experience is combined with previous research showing that bargaining experience matters, our results may overstate the significance of bargaining for an average house. Fortunately, if all segments of the market are perfectly competitive then the process of selection should not bias the testing procedure.

Results

Table 2 reports the estimated coefficients for equations (4) and (5). The low R² in the left hand regression indicates that most of the variation in \( \log(p_{2}/p_{1}) \) is not explained by changes in general conditions, such as inflation; it is idiosyncratic to the seller. The coefficient on DDOP in the right hand regression is significantly different from 0 and strongly supports the hypothesis that a seller can influence the selling price of their house.
Table 2: List Price and Selling Price Functions

Dependent Variables: \( \log(p_{2}^L/p_{1}^L) \) and \( \log(p_{2}^S/p_{1}^S) \)

<table>
<thead>
<tr>
<th></th>
<th>List Price</th>
<th></th>
<th>Selling Price</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>t-statistic</td>
<td>Coefficient</td>
<td>t-statistic</td>
</tr>
<tr>
<td>Constant</td>
<td>0.07</td>
<td>3.13</td>
<td>0.09</td>
<td>9.83</td>
</tr>
<tr>
<td>( \tau 93 )</td>
<td>0.01</td>
<td>0.45</td>
<td>-0.01</td>
<td>-1.02</td>
</tr>
<tr>
<td>( \tau 94 )</td>
<td>0.02</td>
<td>0.63</td>
<td>0.01</td>
<td>0.87</td>
</tr>
<tr>
<td>( \tau 95 )</td>
<td>0.01</td>
<td>0.25</td>
<td>0.01</td>
<td>1.09</td>
</tr>
<tr>
<td>( \tau 96 )</td>
<td>0.01</td>
<td>0.51</td>
<td>0.01</td>
<td>0.60</td>
</tr>
<tr>
<td>( \tau 97 )</td>
<td>-0.01</td>
<td>-0.17</td>
<td>-0.01</td>
<td>-0.51</td>
</tr>
<tr>
<td>( \tau 98 )</td>
<td>-0.03</td>
<td>-0.86</td>
<td>-0.07</td>
<td>-4.65</td>
</tr>
<tr>
<td>( \tau 99 )</td>
<td>-0.03</td>
<td>-1.15</td>
<td>-0.02</td>
<td>-2.00</td>
</tr>
<tr>
<td>Diff. between FXR</td>
<td>0.12</td>
<td>0.59</td>
<td>0.33</td>
<td>4.00</td>
</tr>
<tr>
<td>Diff. between UR</td>
<td>-0.01</td>
<td>-1.93</td>
<td>-0.01</td>
<td>-5.44</td>
</tr>
<tr>
<td>Diff. between REAL5</td>
<td>-0.00</td>
<td>-0.25</td>
<td>0.00</td>
<td>1.57</td>
</tr>
<tr>
<td>Diff. between SALES</td>
<td>-0.00</td>
<td>-1.47</td>
<td>-0.00</td>
<td>-1.69</td>
</tr>
<tr>
<td>Diff. between BALANCE</td>
<td>0.06</td>
<td>1.23</td>
<td>0.05</td>
<td>2.56</td>
</tr>
<tr>
<td>DDOP (i.e. ( \delta ))</td>
<td>--</td>
<td>--</td>
<td>0.98</td>
<td>58.43</td>
</tr>
<tr>
<td>N. Obs</td>
<td>621</td>
<td></td>
<td>621</td>
<td></td>
</tr>
<tr>
<td>R^2</td>
<td>0.073</td>
<td></td>
<td>0.861</td>
<td></td>
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</tbody>
</table>

For most years, the house price inflation rate is low, roughly equal to the general inflation rate and is roughly equal in the two regressions. Only the unemployment rate has a significant effect on the list price but many indicators affect the selling price. A positive coefficient indicates that an increase in the relevant variable increases the second selling price relative to the first: e.g. a higher local unemployment rate during the second sale is predicted to decrease the selling price and a move toward a seller’s market (i.e. an increase in DBALANCE) is predicted to increase the selling price. Even so, indicators of market conditions explain little of the variation in the dependent variables. If the indicators are omitted, the \( R^2 \) of the two equations fall from 0.073 and 0.861 to 0.063 and 0.858.

We repeated the analysis for 9 different areas within the city. With the exception of one area, the lowest estimated value of \( \delta \) was 0.892 and the highest estimate was 1.151. The estimate for the exceptional area was less than 0.58 but this estimate rose to 0.75 after excluding one observation, whose DDOP was more than three standard deviations away from the mean. Thus the possibility that one area may contaminate the analysis because only it became “hot” should be of little concern.
To study the issue raised at the close of the last section, we reduced the data by about two-thirds to focus on high-value houses (in this case, houses with a list price above $130,000 in 1999). Using the same two-step procedure, we found that the estimated value of $\hat{\delta}$ was 0.87 and significantly different from 0. We conclude that segmentation has little effect on the link between DOP and selling price.

The left hand pair of columns in Table 3 reports the coefficients estimated using equation (7). They confirm the findings of Table 2. Not only does the coefficient on $\log(p_{L1}/p_{L2})$ differ from 0, but all of the other coefficients are statistically and economically close to zero, as expected if $\hat{\delta}$ is close to 1. The difference in $R^2$ between the regressions reported in this table shows that including $\log(p_{L2}/p_{L1})$ in the regression adds substantial explanatory power.

Multicollinearity amongst the regressors in the left hand columns is not an issue since the $R^2$ of the left hand equation reported in Table 2, which involves all of these variables and more, is less than 0.1.

Table 3: Evidence for Rejecting Price-taking Behaviour

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>t-statistic</th>
<th>Coefficient</th>
<th>t-statistic</th>
</tr>
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<tbody>
<tr>
<td>$\tau_{93}$</td>
<td>0.0014</td>
<td>0.40</td>
<td>0.0125</td>
<td>1.3</td>
</tr>
<tr>
<td>$\tau_{94}$</td>
<td>-0.0007</td>
<td>-0.07</td>
<td>0.0563</td>
<td>2.1</td>
</tr>
<tr>
<td>$\tau_{95}$</td>
<td>0.0062</td>
<td>0.62</td>
<td>0.0151</td>
<td>0.6</td>
</tr>
<tr>
<td>$\tau_{96}$</td>
<td>-0.0035</td>
<td>-0.38</td>
<td>-0.0030</td>
<td>-0.1</td>
</tr>
<tr>
<td>$\tau_{97}$</td>
<td>0.0073</td>
<td>0.66</td>
<td>0.0137</td>
<td>0.5</td>
</tr>
<tr>
<td>$\tau_{98}$</td>
<td>0.0041</td>
<td>0.46</td>
<td>-0.0272</td>
<td>-0.9</td>
</tr>
<tr>
<td>$\tau_{99}$</td>
<td>0.0030</td>
<td>0.40</td>
<td>-0.0105</td>
<td>-0.5</td>
</tr>
<tr>
<td>$\log(p_{L2}/p_{L1})$</td>
<td>0.987</td>
<td>59.14</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Constant</td>
<td>--</td>
<td>--</td>
<td>0.0882</td>
<td>4.0</td>
</tr>
<tr>
<td>N. Obs</td>
<td>621</td>
<td>621</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.858</td>
<td>0.063</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Finally and for several reasons, we include Table 4 which considers different time periods. The first reason is that the time path of house prices may display autocorrelation.

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7 Because this regression does not include a constant, the value of $R^2$ for the left hand regression normally computed by the statistical package is unreliable. The computed value has been replaced with a direct calculation.
Liquidity of a Real Estate Market (Capozza, Hendershott, Mark and Meyer, 2002). Since real estate agent decide on a list price by referring to the selling prices of recently-sold houses, a change in selling prices of recently sold houses might cause a change in list prices of houses newly offered for sale. Secondly, the selection of types of houses present in the repeat sales data set may vary over time. Relatedly, correlation between $\log(p_{S1}/p_{S2})$ and $\log(p_{L1}/p_{L2})$ may be caused by omitted variables, i.e. undetected renovations of the houses or changes in neighbourhood characteristics. Though the data set focuses on houses with no renovation, some renovated houses might have been included by accident. Since the probability that these events occurred would vary with time, the presence of this kind of omitted variable could cause a pattern in the results.

In fact, spurious correlation between the list price and the selling price should not be of little practical concern since the inflation was relatively low during the time period used in this study the average annual national inflation rate was about 1.5 percent) and since Tables 2 and 3 already show that time has little effect on prices.\textsuperscript{5} To verify this conjecture, consider a more direct test which emphasizes cross-sectional variation; consider subsamples of houses first sold in the same year. Since our use of annual subsamples implies that any difference in market conditions between the sample year and year of the second sale (1999) will be roughly constant within a subsample, we regress $\log(p_{S1}/p_{S2})$ on only $\log(p_{L1}/p_{L2})$ and a constant. Using data from the four years having large numbers of observations, Table 4 shows that the estimate of $\delta$ and $R^2$ are comparable to what was reported in Table 2 with no apparent time trend. The final column is included to show that variation in the independent variable is large relative to the estimated local house price inflation rates shown in Table 2. We conclude that, even if a housing cycle affects the level of prices, it has little effect on the ability of an individual seller to raise or lower their selling price relative to other sellers.

\textsuperscript{5} Table 4 reinforces a conclusion drawn from an analysis of the source data: that the distribution of DDOP varies little over the years and that the distribution of DDOP is not bimodal. Thus, time-varying omitted variables are not a serious issue.
Liquidity of a Real Estate Market

Table 4: Variation over Time

\[ \log(p^s_2/p^s_1) = \mu + \delta \log(p^l_2/p^l_1) \]

<table>
<thead>
<tr>
<th>Sample Year (prior to 1999)</th>
<th>(\mu)</th>
<th>(\delta)</th>
<th>(R^2)</th>
<th>N. Obs.</th>
<th>St. Dev. of (\log(p^l_2/p^l_1))</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 years prior</td>
<td>0.002</td>
<td>1.129</td>
<td>0.882</td>
<td>100</td>
<td>0.113</td>
</tr>
<tr>
<td></td>
<td>(0.4)</td>
<td>(27.1)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 years prior</td>
<td>0.015</td>
<td>0.948</td>
<td>0.831</td>
<td>133</td>
<td>0.107</td>
</tr>
<tr>
<td></td>
<td>(3.2)</td>
<td>(25.4)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 years prior</td>
<td>0.016</td>
<td>0.950</td>
<td>0.839</td>
<td>122</td>
<td>0.103</td>
</tr>
<tr>
<td></td>
<td>(3.5)</td>
<td>(25.0)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 years prior</td>
<td>0.007</td>
<td>1.023</td>
<td>0.873</td>
<td>113</td>
<td>0.103</td>
</tr>
<tr>
<td></td>
<td>(1.3)</td>
<td>(27.7)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Implications

This research implies that a single seller can raise the price of their house. We found that an increase in the Degree of Over-Pricing by one percentage point increased the selling price by about one percent. Our analysis used a data set includes only houses with little or no renovation between sales. Since Table 2 includes variables which control for local market conditions and the general rate of inflation, the only unexplained difference between the two sales of each house should be the identity of the seller. Our conclusion is confirmed by estimating the relationship using various partitions of the data. The fact that the findings are consistent with each other and with what was reported in Table 2 help to confirm the validity of the two-step process.

Evidence that a seller can raise their own selling price does not prove that sellers behave optimally. In all cases, sellers must bargain wisely to achieve a selling price that is acceptable to both the buyer and the seller. And, as noted in footnote 1 and illustrated in Figure 2, a seller must trade off the advantages of a higher selling price against the disadvantages of a longer time-till-sale and the possibility of not selling to any buyer. These dimensions can be economically significant since Anglin (1994) reported that 30 to 50 percent of negotiations ended without a transaction and Anglin, Rutherford and Springer (2003) noted that about 40 percent of house listings ended without a sale. A formal test of optimizing behaviour requires a different data set and an econometric methodology which combines the two dimensions of the selling process shown in Figure 2 at the same time as it separates the omitted variable problem from the
Our research suggests three other directions worthy of future study. First, there is the question of whether the effect of an increase in DOP is the same in all markets. Even if one doubts the magnitude of our estimate, the difference between the \textit{difference} in $R^2$ between the regressions reported in Table 3 shows that including some information on the list price adds substantial explanatory power. The analysis uses ordinary least squares even though the logic used to derive the key equation suggests that the distribution of errors may be more complex than is usually assumed. This fact suggests that the efficiency of the estimators could be improved. Regardless, the large t-statistics reported here suggest that the conclusion is unlikely to be reversed. Another weakness of this analysis is that it relies on an approximation to produce a simple expression with no omitted variables. The nature of the approximation does not restrict the effects of omitted variables, since the number of variables used as $X$ in equation (1) is unrestricted, but it may restrict the interaction between omitted variables and the Degree of Over-Pricing. Removing this restriction might be interesting but, because interaction terms become important only if an effect exists, refining the analysis would not change the conclusion that DOP has a measurable effect on the selling price.

Second, existing theory provides little guidance on which indicators of market conditions are best. We selected indicators that are commonly used by professionals where the ratio of sales to new listings (BALANCE) might measure excess demand. The usual problem with including additional indicators is that the most desirable information, i.e. on the behaviour of house buyers, is extremely hard to obtain on a regular basis.

\footnote{Some readers may be interested in the relationship between the Degree of Over-Pricing and the discount. The discount is often used by real estate professionals because it automatically controls for omitted variables that affect the list price and selling price simultaneously. In Anglin and Wiebe’s (2002) study of time-till-sale in the Windsor housing market, they were able to estimate DOP for different houses at a point in time and a simple OLS regression of the discount on DOP and a constant produced $R^2=0.0059$. Given that $\hat{\delta}$ is estimated to be close to 1, this finding should not be a surprise.}
Finally, there remains the classic question of whether the price mechanism produces an efficient allocation of resources. Hosios (1990), Pissarides (2000) and Anglin and Arnott (1999) studied different aspects of this problem in models that are compatible with the kind of uncertainty discussed by Arrow (1959). In spite of evidence to the contrary, these models assume that any seller who enters the market eventually sells to a buyer. Nobody has studied whether the price mechanism can allocate resources efficiently in an illiquid market with sellers who test the market price, and sometimes fail to sell.
Bibliography


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