The Benefit of Search in Housing Markets

Authors

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Abstract

Unlike in an efficient market where buyers and sellers are mere price-takers, participants in the real estate market are able to influence ultimate transaction prices through individual search efforts. Such benefit can offset the negative price trend of a declining market and compound the positive price trend of a growing market, suggesting an asymmetric effect of the price and time-on-the-market (TOM) relation. In other words, search mitigates the downside risk and magnifies the upside potential for the seller, which is an important advantage for real estate investors. In this study, we uncover the asymmetric price–TOM relation, and demonstrate the value of search using empirical data from the residential real estate market. Based on a large sample of home sales in the Virginia Beach–Norfolk, Virginia metropolitan area during an extended period of time, our findings clearly reveal an asymmetric search effect on price: longer TOM is strongly correlated with higher selling prices, but more interestingly, even in a declining market, the effect of the search (or the impact of TOM) on price is still positive, albeit smaller, suggesting the benefit of search is more than enough to potentially offset a negative market impact.

There is little doubt that the private real estate market is much less efficient than the publically traded financial market. But market inefficiency, though implies trading difficulties to some, may present opportunities to others who are able to exploit such inefficiencies to their advantage. In the more efficient security markets, buyers and sellers are merely price-takers, but in the inefficient real estate market, individuals’ buying and selling efforts, as well as their ability to search for and bargain with the desirable trading counterparts can significantly alter ultimate trading prices. Such ability could prove to be an advantage to property investors during both good and bad market conditions.

For example, the residential real estate transaction process is typically characterized by a sequential search and random match between buyers and sellers. The classical search model can be used to forecast a positive correlation between search effort [typically measured by time-on-market (TOM)] and selling price; a longer selling time is likely to result in higher selling prices. This implies
property sellers must often face a necessary trade-off: to either sacrifice price for a relatively quick sale, or spend additional time searching for a (possibly) better price. Thus, the possibility that individual sellers can influence market price through their search efforts should not be overlooked.

This is an important difference between the real estate market and a more efficient market where individual investors are merely price-takers. In the latter market, the relation between price and selling time is straightforward: In a good market when prices are rising, the longer the investor waits the higher price he is likely to receive—a positive price–TOM correlation. Likewise, in a bad market where prices are falling, a longer waiting time will lead to a lower selling price—a negative price–TOM correlation. In such a market, the investor is at the mercy of market forces and his only control is to decide to sell now or to wait to sell later. However, the real estate market is different because individual effort can affect the selling price. Since longer search time is likely to lead to a higher selling price, the search effect will enhance the positive impact of an up market, and offset (partially or in full) the negative impact of a down market. In other words, the interaction between market condition and search time has an asymmetric impact on price. The possibility of obtaining a better price through search effort in times of market decline enables investors to limit their downside risk exposure. This is an important advantage to investing in the inefficient real estate market.

In this paper, we attempt to uncover such an asymmetric price–TOM relation, and to demonstrate the value of search with empirical data from the residential real estate market. Using a large sample of residential sales in the Virginia Beach–Norfolk, Virginia metropolitan area during 2004–2011, we examine the price–TOM relation during both up and down market cycles. As with many areas around the country, the housing market in the Virginia Beach–Norfolk area went through a rapidly growing period from 2004 to 2006, a transitory period in 2007, followed by a rapidly declining period from 2008 to 2011. This provides an excellent opportunity to observe the dynamic interaction between price and selling time under changing market conditions. Our findings clearly reveal an asymmetric search effect on price. In a growing market, more search effort (longer TOM) is strongly correlated with higher selling prices. But more interestingly, even in a declining market, the effect of the search (or the impact of TOM) on price is still positive, albeit smaller, suggesting the benefit of search is significant in offsetting negative market impact.

This finding expands the price–TOM literature as follows. Traditionally, the effect of TOM on price is often examined under various trading conditions, such as seller motivation, foreclosure status, property heterogeneity, the assistance of brokers, the utilization of the Internet, and so forth. Typically, the effects of these factors on price and selling time are of primary interest, and the price–TOM relation is only interpreted to the extent the regression coefficient is positive or negative. While the literature is too large to be reviewed in its entirety, an excellent summary can be found in Sirmans, Macpherson, and Zietz (2005), who enumerate the results of 27 papers that examined the price–TOM relation in various contexts.
Among them, two studies concluded positive relations, 12 revealed negative relations, and the remaining 13 found no significant relations. An expanded literature search would easily reveal many more of these types of studies. To mention a few, Elder, Zumpano, and Baryla (1999) study the effect of broker assistance on home buyer’s search duration and find that the buyer’s opportunity costs play a significant role in buyer’s search intensity and the actual search duration. Brastow, Springer, and Waller (2012) study the compensation scheme on seller-agent effort with regard to selling time, probability of sale, and selling price. They find that properties within an individual broker’s GIS-determined service area are more likely to sell, sell faster, and sell with an associated price premium. These effects are more concentrated in the market for higher priced homes. Baryla, Zumpano, and Elder (2000) examine the effect of buyer search under varying market conditions, and find search duration is critically affected by economic conditions. Richardson and Zumpano (2012) examine the use of the Internet on buyer search efforts and find that Internet searches increase buyer search intensity as well as search duration, suggesting that the use of the Internet may slow down the transaction process. Turnbull and Zahirovic-Herbert (2011) investigate whether vacant homes sell more slowly and at lower prices. They find that robust vacancy effects on price and liquidity across all market phases primarily reflect greater seller holding cost and diminished bargaining power. Overall, these studies are less interested in the interaction between price and TOM, and instead are more focused on how the two variables are affected by some exogenous factors. As such, they do not directly address the mixed findings on the price–TOM correlation.

A recent work by An, Cheng, Lin, and Liu (2013) attempted to reconcile the conflicting findings at both the theoretical and empirical levels. Taking the two most relied upon but seemingly contradicting theories, the classical search model (where a positive price–TOM correlation is posited) and Lazear’s (1986) clearance model (where a negative price–TOM correlation is posited), the authors show that when both theories are extended to varying market conditions, they yield consistent rather than contradicting predictions. That is, the price–TOM relation can be positive, negative, or insignificant depending on the market conditions under which the transactions occur. This theoretical result is also supported by their empirical analysis, which examined a large sample of REO sales across a large number of local markets during a two-year period (2003–2004). By categorizing local housing market conditions into multiple tiers ranging from rapidly declining to rapidly growing in home prices, they find that the price–TOM relation is mostly positive except in the rapidly declining markets where the relation turns negative. They further show that the magnitude of the search effect is monotonically bigger as market conditions improve from modestly declining to rapidly growing.

Prior to An, Cheng, Lin, and Liu (2013), most previous studies typically use a cross-sectional sample of sales data from concentrated market areas during a short period of time (often a year or two). The purpose is to control the impact of
market conditions as opposed to understanding how different market conditions affect the price–TOM relation. Although An, Cheng, Lin, and Liu (2013) use a cross-sectional sample as well, the diverse geographic distribution of the data enables the authors to identify distinct market conditions among local markets in which individual sales occurred, and to demonstrate that, depending on market conditions, the price–TOM correlation can indeed be anything (positive, negative, or insignificant).

In this study, we are not concerned about whether the price–TOM relation is positive or negative. Rather, our interest is in how individual search effort (TOM) interacts with market forces to affect the ultimate selling price. While such interaction can lead to either a positive or negative price–TOM correlation, the correlation has to be asymmetric. Such asymmetry reflects the value of individual search effort that benefits investors in both the up and down markets. Beyond the primary research objective, this study differs from An, Cheng, Lin, and Liu (2013) in two other aspects. First, their sample, although large, is still cross-sectional in nature, and does not cover a complete market cycle. Because of the heterogeneous performances of local housing markets, they were able to categorize the markets into different growth tiers. Our sample, on the other hand, is geographically concentrated but spans a much longer time period where the market actually experienced significant up and down cycles. Such a data set allows for a more direct examination of the search effect on price in varying market conditions. Second, the data used in An, Cheng, Lin, and Liu (2013) are REO sales. While the REO market warrants serious research, especially in recent years, it is widely perceived that the REO market may work differently from the normal market so that the findings in the REO market may not be generalized to the entire market. The current study overcomes this data limitation by gathering a large sample of normal home sales; thus, the findings will have broader implications.

The rest of the paper is organized as follows. After a review of the classical search models and related studies, we present an extension of the static search model to dynamic market conditions by incorporating the impact of macro market conditions on micro search behavior. We next describe the data and present a series of regression analyses that lead to the empirical findings of this study. We close with concluding remarks.

Search Models and Related Literature

There is a rich body of literature on search theory (e.g., Gal, Landsberger, and Levyskon, 1981; Morgan and Manning, 1985; Mckenna, 1986). Search theory was initially developed in the field of labor economics and later adapted to the study of real estate and other illiquid assets. It is an influential economic theory that is often applied to study the job-seeking process of individuals in the labor market where, as in the real estate market, the central problem facing the seller (the job seeker) is how to determine the optimal strategy in choosing among a series of buyers (employers) whose arrival and offering price are both random. Yinger
(1981) was perhaps the first to apply the search model to study the real estate transaction process.

Recognizing search as a fundamental feature of the market for illiquid assets, Lippman and McCall (1986, p. 44) employ the search model to study a broader question: What is an asset's liquidity and how can we measure it? In a formal analysis, they propose an operational measure of liquidity—"the expected time until the asset is sold when following the optimal policy." Although the concept is generally regarded as valid for a wide range of assets, such as collectibles, jewels, precious metals, artwork, various capital goods, etc., it is in the real estate field that the Lippman-McCall liquidity definition, commonly known as the time-on-market (TOM), has been most widely accepted as a formal measure of liquidity.

Theoretical and empirical studies examining the concept within the search paradigm generally confirm a positive price–TOM relation. Besides Lippman and McCall (1986), studies such as Haurin (1988) and Yavas and Yang (1995) take formal approaches to formalize the intuition that longer selling time increases the probability of encountering buyers with higher offers. On the empirical side, Forgey, Rutherford, and Springer (1996) provide some evidence for an optimal marketing period and indicate that liquidity is priced into single-family home sales. Homes with higher selling prices tend to have longer expected TOM. Genesove and Mayer (1997) find that owners of properties with higher loan-to-value ratios tend to wait longer and receive higher prices than properties with lower loan-to-value ratios. Rutherford, Springer, and Yavas (2005) and Levitt and Syverson (2008) investigate the sales of properties owned by real estate brokers and find broker owned houses tend to stay on the market longer and sell at higher prices. Collectively, these studies support the notion that the relation between price and TOM is positive. Lately, though, this view has been expanded by An, Cheng, Lin, and Liu (2013) that, when examined under varying market conditions, the price–TOM relation can be positive, negative, or insignificant, depending on the market condition of observed data.

**Search under Dynamic Market Conditions**

Until fairly recently, the application of search models has largely been limited to providing directional guidance for empirical studies on the price–TOM relation. Advancement toward formal quantification of such a relation has been made in recent studies such as Lin and Vandell (2007) and Cheng, Lin, and Liu (2008). These studies differ in the stopping rules being assumed in the search process. Whereas Lin and Vandell (2007) assume the search process is one whereby the seller accepts the first offer above his reservation price, Cheng, Lin, and Liu (2008) assume such process to be one of sequential search with recall, in which a seller is able to recall and select the highest offer available among a group of previously rejected bids. Both studies extend the literature beyond directional discussions and develop closed-form formulae for quantifying the impact of TOM on property

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selling price. However, they are both confined within a static market condition in which the bidding price distribution is unchanged. In reality, as market condition changes, potential buyers’ valuation of properties will adjust accordingly so the bidding price distribution is not static. In the remainder of this section, we provide a brief extension of the models employed in these two studies under dynamic market conditions.

To briefly describe the model of Cheng, Lin, and Liu (2008), consider a seller who places a real estate asset on the market at time 0. Suppose the seller chooses the listing price as \( P \). The buyer’s stochastic arrival is assumed to follow a Poisson process at rate \( \lambda \). As in Lin and Vandell (2007), Yavas (1992), and Read (1988), they further assume that the bidding price is uniformly distributed over \([P, \bar{P}]\). Suppose that \( t_i \) is the waiting time between the arrival of buyers \( i - 1 \) and \( i \), the TOM of waiting for the \( n \)th buyer then satisfies \( TOM = \sum_{i=1}^{n} t_i \). At time \( TOM \), the seller has received \( n \) offers. If recall is allowed, the seller will receive the highest bidder among them. In reality, some earlier bidders may find other appropriate houses and are no longer interested in the house, and thus exit the bidding pool. They denote \( \theta \) as the probability of a bidder staying open for recall, thus \( (1 - \theta) \), where \( 0 \leq \theta \leq 1 \) is the probability of the bidder exiting the bidding process. A higher \( \theta \) implies fewer exiting bidders and a smaller supply of similar houses, hence a tighter housing market. In the extreme case where \( \theta = 1 \), no buyer exits the bidding and the situation would be one of perfect recall.

Cheng, Lin, and Liu (2008) show the relation between sales price and TOM as follows:

\[
E[P] = (P_{bid} + \sqrt{3}\sigma_{bid}) - \frac{2\sqrt{3}}{\lambda E[TOM]\theta + 1} \sigma_{bid},
\]

where \( P_{bid} \) and \( \sigma_{bid} \) are the expected bidding price and its volatility, respectively.

The assumption that the bid distribution is time-invariant is over-simplified. In reality, the housing market moves in cycles, experiencing ups and downs over time. In order to capture the effect of market change on the bidding distribution, a more realistic assumption for the bidding distribution at time marketing period (TOM) is over \([\bar{P} + \Delta \times TOM, \bar{P} + \Delta \times TOM]\). When \( \Delta > 0 \), the bidding price should be adjusted upward to reflect the effect of improving market conditions on the property value. When \( \Delta < 0 \), the opposite will be true. Intuitively, the probability of a bidder exiting the process mainly depends on the availability of suitable substitute properties. In a hot market (\( \Delta > 0 \)) where suitable alternatives are in short supply, bidders tend to have a lower probability to exit, implying a higher \( \theta \), while the opposite is true in a cold market. In other words, \( \theta \) is a function of \( \Delta \) and \( \partial \theta(\Delta) / \partial \Delta > 0 \). Under changing market conditions, we can show that the relation between sales price and TOM becomes:
The second term on the right-hand side of equation (2) captures the benefit of search, i.e.,

$$E[P] = (P_{bid} + \sqrt{3}\sigma_{bid}) - \frac{2\sqrt{3}}{\lambda E[TOM] \theta(\Delta) + 1} \sigma_{bid} + \Delta \times E[TOM]. \quad (2)$$

And the third term on the right-hand side of equation (2) captures the impact of the overall market conditions on the search, i.e.,

$$\frac{\partial \left\{ \frac{2\sqrt{3}}{\lambda E[TOM] \theta(\Delta) + 1} \right\}}{\partial E[TOM]} = \frac{2\sqrt{3}\sigma_{bid}\lambda \theta(\Delta)}{[\lambda E[TOM] \theta(\Delta) + 1]^2} > 0. \quad (3)$$

Two points are worth noting from equations (2)–(4). First, when the market improves over time (i.e., \( \Delta > 0 \)), both the benefit of search and the impact of overall market conditions on the search are positive. Therefore, there is a positive relation between sales price and TOM.

Second, when market conditions deteriorate significantly (i.e., \( \Delta < 0 \)), it is highly likely that the benefit of search may not match with the adverse impact of market conditions on property value such that:

$$\frac{2\sqrt{3}\sigma_{bid}\lambda \theta(\Delta)}{[\lambda E[TOM] \theta(\Delta) + 1]^2} + \Delta < 0. \quad (5)$$

If this occurs, the relation between sales price and TOM would become negative.

The models of Lin and Vandell (2007) are more straightforward. They study the price–TOM relation under the scenario of selling without recall, and find the relation between sales price and TOM can be expressed as follows:
Under changing market conditions, we can show the relation between sales price and TOM becomes:

\[ E[P] = E[P_{BID}] + \sqrt{3}E[TOM]\sigma_{BID}, \]  

Similarly, we can draw two conclusions from equation (7). First, when markets improve over time (i.e., \( \Delta > 0 \)), both the benefit of search \( (\sqrt{3}E[TOM]\sigma_{BID}) \) and the impact of the overall market conditions on search \( (\Delta \times E[TOM]) \) are positive. Therefore, there is a positive relation between sales price and TOM.

Second, when market conditions deteriorate significantly, it is possible that:

\[ \sqrt{3}\sigma_{BID} + \Delta < 0. \]  

In this case, we would observe that the relation between sales price and TOM becomes negative. In either case, it is easy to see that the magnitude (or absolute value) of \( |\sqrt{3}\sigma_{BID} + \Delta| \) is greater when \( \Delta > 0 \) (up market) than it is when \( \Delta < 0 \) (down market), hence the asymmetric impact of TOM on price.

In summary, the intuition of search under changing market conditions is straightforward. In an inefficient market where information takes time to disseminate among market participants, reasonable search effort (indicated by TOM) is beneficial because it increases the chance of encountering higher bids. This benefit is enhanced when the market is also going up, but is offset to some extent by the negative impact of market decline. In the end, whether the relation is positive or negative in a declining market depends on which impact (market conditions versus search effort) dominates the other. After all, because search is a microeconomic behavior, its outcome must be subject to the influence of macro market conditions. In the remainder of this paper, we empirically examine how the relation between sales price and TOM varies over market conditions.

**Data**

The data set for our analysis contains a large sample of residential sales from the Virginia Beach–Norfolk MSA from the 2004:Q1 to 2011:Q3 period. Since this period is marked by rapidly growing (2004–2006), transitory (2007), and declining (2008–2011) sub-periods, the data allow us to examine the impact of search on selling price under different market conditions. After removing observations with
missing values, our final sample contains 217,117 home sales, of which 158,288 are single-family detached houses and 58,829 are attached houses. The variables contained in each observation are shown in Exhibit 1.

These variables capture many physical and locational attributes of the properties. Taking advantage of our large and information-rich sample, we are not only able to control those variables that are common in hedonic models such as lot size, living area, number of bedrooms and bathrooms, pools and fireplaces, etc., but also to control for 13 types of flooring, 26 types of heating systems, 22 parking types, and 19 types of various waterfront and view features. This level of detailed control is typically unattainable by most hedonic pricing models.

The data clearly indicate the local housing market went through an up and down cycle. During the three years prior to 2007, the market showed a double-digit growth each year, averaging 18.8% annually. The market’s fast growth was halted in 2007, showing only a modest 1.38% price growth that year, before it turned
Exhibit 2 | Market Conditions in Virginia Beach–Norfolk Area

<table>
<thead>
<tr>
<th>Period</th>
<th>Annual HP Growth</th>
<th>Market Cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004–2006</td>
<td>18.8%</td>
<td>Up</td>
</tr>
<tr>
<td>2007</td>
<td>1.38%</td>
<td>Transition</td>
</tr>
<tr>
<td>2008–2011</td>
<td>−3.9%</td>
<td>Down</td>
</tr>
</tbody>
</table>

Note: The source is the Federal Housing Finance Agency.

south declining about 3.9% annually during the next four years. The abrupt slowdown in 2007 can be viewed as a transitory period, for this is the year that the local housing market conditions shifted from rapid growth to decline (see Exhibit 2). Therefore, to understand the impact of market conditions on the price–TOM relation, we conduct two “full sample” analyses. In one analysis, we use all data. In the second analysis, we remove those transactions whose marketing time had any overlap with 2007, which include 9,745 transactions that were listed prior to 2007 but either sold in or after 2007, as well as 38,809 transactions that were listed in 2007 and sold either in or after 2007, thus leaving a total of 168,563 observations for the analysis (217,117 − 9,745 − 38,809 = 168,563), of which 123,669 are detached houses and 44,894 are attached houses. The sample breakdown and summary statistics are in Exhibit 3.

Regression Analysis

The traditional way to model the price–TOM relation is through a hedonic approach. A typical hedonic model that is frequently found in the literature takes the following general form:

\[ \text{Model 1: } \ln(\text{Price}) = \alpha X + \beta \text{SeasonVolume} + \gamma \text{TOM} + \epsilon, \quad (9) \]

where the logarithm of sales price is regressed over vectors of independent variables including property characteristics (X), SeasonVolume that contains variables indicating the year and quarter of the sale, as well as the total sale volume in each quarter, and time-on-market (TOM). In the past, many studies avoid the control of market conditions by deliberately drawing data samples from a concentrated area over a short period of time during which the market conditions can be assumed to be constant. Obviously, the price–TOM relation observed in this way is time- and market-specific and may not be generalized to different times and markets. Other studies typically control for market conditions with seasonality and some macroeconomic measures or proxy variables such as sales
### Exhibit 3 | Summary Statistics and Sample Breakdown

<table>
<thead>
<tr>
<th>Variables</th>
<th>Full Sample: Detached Houses</th>
<th>Full Sample: Attached Houses</th>
<th>Excluding Transitory Data: Detached Houses</th>
<th>Excluding Transitory Data: Attached Houses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (std. dev.) sale price ($)</td>
<td>268,857 (167,497)</td>
<td>206,472 (167,497)</td>
<td>260,303 (162,775)</td>
<td>197,825 (167,497)</td>
</tr>
<tr>
<td>Mean (std. dev.) living area (sf)</td>
<td>1,919 (865)</td>
<td>1,420 (486)</td>
<td>1,902 (878)</td>
<td>1,410 (501)</td>
</tr>
<tr>
<td>Mean (std. dev.) bathroom (#)</td>
<td>2.18 (0.76)</td>
<td>2.17 (0.57)</td>
<td>2.18 (0.77)</td>
<td>2.17 (0.55)</td>
</tr>
<tr>
<td>Mean (std. dev.) bedroom (#)</td>
<td>3.53 (0.81)</td>
<td>2.56 (0.65)</td>
<td>3.53 (0.81)</td>
<td>2.57 (0.64)</td>
</tr>
<tr>
<td>Mean (std. dev.) lot size (acre)</td>
<td>0.18 (0.07)</td>
<td>0.01 (0.01)</td>
<td>0.18 (0.07)</td>
<td>0.01 (0.01)</td>
</tr>
<tr>
<td>Mean (std. dev.) property age (yr)</td>
<td>31.0 (25.6)</td>
<td>17.2 (15.0)</td>
<td>31.8 (25.7)</td>
<td>17.4 (14.9)</td>
</tr>
<tr>
<td>Mean (std. dev.) DOM (day)</td>
<td>112.8 (90.8)</td>
<td>105.9 (99.9)</td>
<td>107.5 (85.4)</td>
<td>98.54 (88.4)</td>
</tr>
<tr>
<td>Mean (std. dev.) sales volume (#)</td>
<td>5,106 (1,595)</td>
<td>1,898 (682)</td>
<td>4,580 (1,569)</td>
<td>1,663 (607)</td>
</tr>
</tbody>
</table>

**Sample Proportions (%):**
- **Ownership and House Type**
  - Fee-Simple: 97.58, 49.25, 97.48, 49.82
  - Condominium: 2.42, 50.75, 2.52, 50.18
<table>
<thead>
<tr>
<th>Variables</th>
<th>Full Sample: Detached Houses</th>
<th>Full Sample: Attached Houses</th>
<th>Excluding Transitory Data: Detached Houses</th>
<th>Excluding Transitory Data: Attached Houses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Season and Year of Sale</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Winter (Jan–Mar)</td>
<td>19.97</td>
<td>20.23</td>
<td>17.31</td>
<td>17.34</td>
</tr>
<tr>
<td>Spring (Apr–Jun)</td>
<td>29.27</td>
<td>28.29</td>
<td>29.35</td>
<td>28.22</td>
</tr>
<tr>
<td>Summer (Jul–Sept)</td>
<td>28.29</td>
<td>27.47</td>
<td>29.38</td>
<td>28.69</td>
</tr>
<tr>
<td>Fall (Oct–Dec)</td>
<td>22.47</td>
<td>24.00</td>
<td>23.96</td>
<td>25.75</td>
</tr>
<tr>
<td>2004</td>
<td>10.03</td>
<td>9.90</td>
<td>12.84</td>
<td>12.98</td>
</tr>
<tr>
<td>2005</td>
<td>12.50</td>
<td>12.60</td>
<td>16.00</td>
<td>16.51</td>
</tr>
<tr>
<td>2006</td>
<td>17.42</td>
<td>14.56</td>
<td>16.36</td>
<td>19.08</td>
</tr>
<tr>
<td>2007</td>
<td>12.78</td>
<td>19.10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2008</td>
<td>14.65</td>
<td>15.37</td>
<td>13.21</td>
<td>14.38</td>
</tr>
<tr>
<td>2009</td>
<td>15.92</td>
<td>14.89</td>
<td>20.24</td>
<td>19.30</td>
</tr>
<tr>
<td>2010</td>
<td>10.84</td>
<td>9.00</td>
<td>13.87</td>
<td>11.77</td>
</tr>
<tr>
<td>2011</td>
<td>5.85</td>
<td>4.58</td>
<td>7.49</td>
<td>6.00</td>
</tr>
<tr>
<td>Total Observations</td>
<td>158,288</td>
<td>58,829</td>
<td>123,669</td>
<td>44,894</td>
</tr>
</tbody>
</table>

Note: “Transitory data” are those transactions whose marketing time had any overlap with 2007, which include 9,745 transactions that were listed prior to 2007 but either sold in or after 2007, as well as 38,809 transactions which were listed in 2007 and sold either in or after 2007, thus leaving a total of 168,563 observations for the analysis (217,117 – 9,745 – 38,809 = 168,563), of which 123,669 are detached houses and 44,894 are attached houses.
volume, or dummy variables indicating the month of sale, etc. In any case, the interest is merely in controlling for market conditions, rather than understanding how different market conditions affect the price–TOM relation.\(^3\)

Therefore, Model 1 is inadequate for our purpose because we want to investigate the impact of different market conditions on the price–TOM relation. As discussed in previous sections, the impact of search effort (TOM) on selling price should vary with market conditions. A more appropriate model should examine the cross-effect of TOM and market condition on price. Thus, we begin by specifying the following regression:

\[
\text{Model 2: \( \ln(\text{Price}) = \alpha X + \beta \text{SeasonVolume} + \gamma (\text{MarketState}) \times \text{TOM} + \epsilon \),}
\]

where \( X \) contains a list of property characteristic variables such as living area, number of bedrooms and bathrooms, lot size, fireplace, swimming pool, property age, age-square, etc. In addition, \( X \) also contains dummy controls for various types of flooring, parking, heating systems, waterfront views, and ZIP Codes. \( \text{MarketState} \) is a dummy variable indicating whether the market is in an up or down cycle as defined in Exhibit 2. The coefficient on TOM, \( \gamma (\text{MarketState}) \), is the variable of primary interest. This model captures the interaction between market conditions and TOM, and allows us to estimate one TOM coefficient for each state of market conditions (as opposed to one average for all market conditions). The expectation is that the coefficient will be significantly positive in an up market, but relatively low positive or negative in down market. That is, the effect of search is asymmetric under varying market conditions.

For the purposes of comparison, we estimate both the “traditional” model (equation (9)) and our alternative model (equation (10)). Besides market conditions, our control variables also include 13 types of flooring, 26 types of heating systems, 22 types of parking arrangements, and 19 types of various waterfront and view features. In addition, we also include ZIP Code as a control for locational impact. Because we have a very large sample size, we are able to control independent variables to this detailed level without jeopardizing the degrees of freedom within the regression models.

We begin by focusing on the detached single-family properties. A full sample regression with the transitory period included produces the results summarized in Exhibit 4. As indicated, the estimated coefficients of the common variables are consistent across the two models, and the signs of the coefficients are generally as we expected.\(^4\) Our primary interest is in the coefficients on TOM. The results show that in the “traditional” model (Model 1), the coefficient on TOM is positive and significant at 1%. Since the selling price is in log form, to interpret the coefficient 0.000172 for TOM in Model 1, Kennedy (1984) suggests that the
### Exhibit 4 | Full-sample Regression Results for Detached Houses

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Traditional Approach</td>
<td>OLS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>10.90</td>
<td>0.0000</td>
<td>10.89</td>
<td>0.0000</td>
</tr>
<tr>
<td>Effect of TOM on Selling Price</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Down market</td>
<td>0.000172</td>
<td>37.4100</td>
<td>0.000131</td>
<td>0.0000</td>
</tr>
<tr>
<td>Up market</td>
<td>0.000162</td>
<td>36.3100</td>
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<td>0.0000</td>
</tr>
<tr>
<td>Property Characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Living Area</td>
<td>0.0002</td>
<td>0.0000</td>
<td>0.0002</td>
<td>0.0000</td>
</tr>
<tr>
<td>Bathroom</td>
<td>0.1313</td>
<td>0.0000</td>
<td>0.1312</td>
<td>0.0000</td>
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<tr>
<td>Bedroom</td>
<td>0.0412</td>
<td>0.0000</td>
<td>0.0410</td>
<td>0.0000</td>
</tr>
<tr>
<td>Lot size</td>
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<td>0.0000</td>
<td>0.0517</td>
<td>0.0000</td>
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<td>Fireplace (Yes)</td>
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<td>0.1132</td>
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<tr>
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</tr>
<tr>
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<td>-0.4055</td>
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</tr>
<tr>
<td>Others</td>
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<td>0.0000</td>
<td>-0.0280</td>
<td>0.0000</td>
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<tr>
<td>Window</td>
<td>-0.1080</td>
<td>0.0000</td>
<td>-0.1080</td>
<td>0.0000</td>
</tr>
<tr>
<td>Property Age</td>
<td>-0.0029</td>
<td>0.0000</td>
<td>-0.0028</td>
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<tr>
<td>Property Age²</td>
<td>-3.58E-07</td>
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<td>-3.57E-07</td>
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<tr>
<td>Ownership Type</td>
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</tr>
<tr>
<td>Fee-simple</td>
<td>0.0594</td>
<td>0.0000</td>
<td>0.0590</td>
<td>0.0000</td>
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<tr>
<td>Sales Volume, Season, and Year of Sale</td>
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<tr>
<td>Log(sales volume)</td>
<td>0.121</td>
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<td>0.120</td>
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</tr>
<tr>
<td>Summer</td>
<td>-0.003</td>
<td>0.2210</td>
<td>-0.002</td>
<td>0.2730</td>
</tr>
<tr>
<td>Fall</td>
<td>-0.005</td>
<td>0.0540</td>
<td>-0.005</td>
<td>0.0640</td>
</tr>
<tr>
<td>Winter</td>
<td>-0.006</td>
<td>0.0110</td>
<td>-0.006</td>
<td>0.0090</td>
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<td>0.143</td>
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<tr>
<td>2006</td>
<td>0.205</td>
<td>0.0000</td>
<td>0.203</td>
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</tr>
<tr>
<td>2007</td>
<td>0.151</td>
<td>0.0000</td>
<td>0.148</td>
<td>0.0000</td>
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<td>2008</td>
<td>0.094</td>
<td>0.0000</td>
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</tr>
<tr>
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<td>0.006</td>
<td>0.3630</td>
<td>0.018</td>
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<tr>
<td>2010</td>
<td>-0.023</td>
<td>0.0000</td>
<td>-0.011</td>
<td>0.0640</td>
</tr>
<tr>
<td>2011</td>
<td>-0.143</td>
<td>0.0000</td>
<td>-0.131</td>
<td>0.0000</td>
</tr>
<tr>
<td>R²</td>
<td>81.13%</td>
<td></td>
<td>81.13%</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** The base (omitted) class of some of the multi-class categorical variables are: “central” in cooling system, “condo” in ownership type, “Spring” in season and “2004” in year of sale. The number of observations in Models 1 and 2 is 1,582,888. The other control variables in Models 1 and 2 are: floor type, heating system, waterfront descriptions, parking, and location at the ZIP Code level.
change of selling price \( (g) \) due to one extra month of TOM can be accurately calculated as \( g = \exp(\hat{\beta} - 1/2 \, \text{var}(\hat{\beta})) - 1 \). Using this formula, we can obtain \( g = 0.0172\% \), which works out to be about 0.52\% \((0.0172\% \times 30)\) per month, indicating that the expected selling price increases by about 0.52\% for one extra month of TOM.\(^5\)

The traditional Model 1 masks the impacts of different market conditions on the price–TOM relation because it effectively means that the expected selling price can increase by about 0.52\% for one extra month of TOM regardless of whether the market is up or down. This does not accurately reflect the TOM effect in either a up or down market in light of the results of Model 2 where we see that, in the up market, the expected selling price will increase by about 0.75\% for one extra month of search, while in the down market the benefit of search is about 0.39\% a month. This confirms our expectation that the search benefit on price is asymmetric, because the benefit of search is enhanced by the upwardly moving market and offset somewhat by the downwardly moving market.

The above regression results warrant further scrutiny for two often discussed issues. The first is the concern that the price–TOM analysis may be endogenously determined. Since endogeneity can cause biased parameter estimates from the ordinary least squares (OLS) regression, the findings based on the previous OLS regressions may not be accurate. The second is the potential sample selection bias due to the fact that the sample contains only sold properties. As such, sellers choosing to stay out of the market (those not having to sell) are eliminated from the analysis. If the subsample of sold properties is not a random sample of the entire population of properties for sale, then our previous estimators are likely to suffer from sample selection bias.

To address the endogeneity issue, we conduct a general form of two-stage least squares regression (2SLS). To correct potential selection bias, we implement the Heckman sample selection model (Heckman, 1979). From our sample data, we are able to identify 139,650 unsold single-family properties. Using these as censored observations, along with the uncensored (sold) properties, we conduct the Heckman process. The results are in Exhibit 5.

Overall, the 2SLS results are fairly consistent with those of the OLS. All the coefficients retain the same sign and most maintain similar magnitudes of statistical significance. But the most noticeable difference is in the coefficients of TOM, which decreased for the down market \( (0.000131 \text{ vs. } 0.000094) \) but increased for the up market \( (0.00025 \text{ vs. } 0.000627) \). As the \( t \)-stat indicates in the 2SLS results, the impact of TOM on price in the down market is no longer significant at the 5\% level. The Heckman process further sharpens the contrast between down and up market states in that the TOM coefficient is further increased from the 2SLS results in the up market, but decreased for the down market. The coefficients on all other variables remain largely unchanged, a sign of stable and robust regression results.
### Exhibit 5 | Comparison of Regression Results: 2SLS vs. 2SLS-Heckman Model

<table>
<thead>
<tr>
<th></th>
<th>Model 2 2SLS</th>
<th></th>
<th>Model 2 2SLS-Heckman Model</th>
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</thead>
<tbody>
<tr>
<td><strong>Intercept</strong></td>
<td>10.88</td>
<td>0.0000</td>
<td>9.94</td>
<td>0.0000</td>
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<td><strong>Effect of TOM on Selling Price</strong></td>
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<td></td>
</tr>
<tr>
<td>Down market</td>
<td>0.000094</td>
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<td>0.000029</td>
<td>0.6950</td>
</tr>
<tr>
<td>Up market</td>
<td>0.000627</td>
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<td>0.000679</td>
<td>0.0000</td>
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<tr>
<td><strong>Property Characteristics</strong></td>
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</tr>
<tr>
<td>Living Area</td>
<td>0.0002</td>
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<td>0.0001</td>
<td>0.0000</td>
</tr>
<tr>
<td>Bathroom</td>
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<td>0.1206</td>
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<tr>
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<td>0.0000</td>
<td>0.0303</td>
<td>0.0000</td>
</tr>
<tr>
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<td>0.1316</td>
<td>0.0000</td>
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<tr>
<td>Swimming pool (Yes)</td>
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<td>0.0000</td>
<td>0.0579</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>−0.4061</td>
<td>0.0000</td>
<td>−0.3065</td>
<td>0.0000</td>
</tr>
<tr>
<td>Others</td>
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<td>0.0000</td>
<td>−0.0041</td>
<td>0.5120</td>
</tr>
<tr>
<td>Window</td>
<td>−0.1076</td>
<td>0.0000</td>
<td>−0.1070</td>
<td>0.0000</td>
</tr>
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<td>−0.0037</td>
<td>0.0000</td>
</tr>
<tr>
<td>Property Age²</td>
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<td>−4.73E-07</td>
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</tr>
<tr>
<td><strong>Ownership Type</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Fee-simple</td>
<td>0.0614</td>
<td>0.0000</td>
<td>0.0286</td>
<td>0.0120</td>
</tr>
<tr>
<td><strong>Sales Volume, Season, and Year of Sale</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Log(sales volume)</td>
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<td>0.0000</td>
<td>0.1193</td>
<td>0.0000</td>
</tr>
<tr>
<td>Summer</td>
<td>−0.0019</td>
<td>0.4060</td>
<td>−0.001</td>
<td>0.7200</td>
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<td>Fall</td>
<td>−0.0046</td>
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<td>−0.004</td>
<td>0.3320</td>
</tr>
<tr>
<td>Winter</td>
<td>−0.0089</td>
<td>0.0000</td>
<td>−0.009</td>
<td>0.0330</td>
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<tr>
<td>2005</td>
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<td>0.0000</td>
<td>0.141</td>
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<tr>
<td>2006</td>
<td>0.1922</td>
<td>0.0000</td>
<td>0.197</td>
<td>0.0000</td>
</tr>
<tr>
<td>2007</td>
<td>0.1329</td>
<td>0.0000</td>
<td>0.137</td>
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</tr>
<tr>
<td>2008</td>
<td>0.1353</td>
<td>0.0000</td>
<td>0.154</td>
<td>0.0000</td>
</tr>
<tr>
<td>2009</td>
<td>0.0478</td>
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<td>0.066</td>
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</tr>
<tr>
<td>2010</td>
<td>0.0194</td>
<td>0.0480</td>
<td>0.038</td>
<td>0.0070</td>
</tr>
<tr>
<td>2011</td>
<td>−0.1000</td>
<td>0.0000</td>
<td>−0.084</td>
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<tr>
<td><strong>R²</strong></td>
<td>81.09%</td>
<td></td>
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</tbody>
</table>

Notes: The base (omitted) class of some of the multi-class categorical variables are: “central” in cooling system, “condo” in ownership type, “Spring” in season and “2004” in year of sale. The number of observations in Model 2 2SLS is 158,288 and is 297,938 in Model 2 2SLS-Heckman Model; in Model 2 2SLS-Heckman Model, there are 139,650 censored observations. The other control variables in the models are: floor type, heating system, waterfront descriptions, parking, and location at the ZIP Code level.
The third analysis we conduct is to remove those transitory data from the sample and repeat the regressions for the full sample. As previously discussed, 2007 appears to be a transitory period during which the market condition shifted from growing to declining. The price and TOM observed from transactions occurring during this period may exhibit a somewhat ambiguous relation. Therefore, we removed a total of 48,554 transactions whose marketing durations have any overlap with 2007, including those either listed and/or sold in 2007, as well as those listed prior to but sold after 2007. The regression results are summarized in Exhibit 6.

The results in Exhibit 6 indicate that, after exclusion of the transitory data, the TOM coefficients in both down and up markets have once again become significantly positive. Both coefficients are greater in magnitude than they are in Exhibit 5, but the up market coefficient is much larger than that of the down market in both the general 2SLS model and the 2SLS-Heckman model, clearly indicating an asymmetric impact of TOM on price. These results provide strong empirical support to our theoretical discussions of the search models above. They confirm that the ability to search by the seller can significantly alter the trading outcome to such an extent that, even when the overall market is declining, additional search effort (or longer TOM) can more than offset the negative market impact and reward the seller with higher selling prices than otherwise. Obviously, when the market is growing, search effort is enhanced by the market impact and leads to even higher prices.

The other variables in the model behave rather consistently in retaining the same signs and similar magnitudes. The number of bedrooms, bathrooms, living area, and lot size are all positively correlated with prices. Given that central air conditioning is the base case for "cooling system," it makes sense that other cooling methods exhibit a negative coefficient. Both Age and Age² show significant negative signs. With regard to the Ownership Type, it is not surprising that fee-simple properties exhibit a price premium over the base class of condominium. In addition, the seasonal effects on price seem strong as well. Relative to the base case of spring, prices tend to be higher in all other seasons, which is consistent with most households' moving behaviors.

Finally, we conduct a separate analysis on attached homes. For brevity, we only report the TOM coefficients and omit the detailed coefficients on other variables (see Exhibit 7). All the other variables maintain the same signs and rather stable coefficients as they were in the full sample analysis. For the full sample analysis (including the transitory data), both the 2SLS and 2SLS-Heckman produced consistent results. They reveal a clear asymmetric TOM effect on price, as both down and up market coefficients are significantly positive. When the transitory data are excluded, however, both models yield insignificant down market coefficients. But the asymmetry of TOM effects remain regardless of the model or data used. Overall the results from the attached homes are very consistent with those from the detached houses, as shown in Exhibits 4 and 5.
## Exhibit 6 | Regression Results After Excluding Transitory Data

<table>
<thead>
<tr>
<th></th>
<th>Model 1 Traditional Approach</th>
<th>Model 2 2SLS</th>
<th>Model 2 2SLS-Heckman Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>P-value</td>
<td>Coeff.</td>
</tr>
<tr>
<td>Intercept</td>
<td>10.88</td>
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<td>10.83</td>
</tr>
<tr>
<td>Effect of TOM on Selling Price</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Down market</td>
<td>0.000172</td>
<td>0.0000</td>
<td>0.000199</td>
</tr>
<tr>
<td>Up market</td>
<td>0.0002</td>
<td>0.0000</td>
<td>0.0002</td>
</tr>
<tr>
<td>Property Characteristics</td>
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</tr>
<tr>
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<td>0.0476</td>
</tr>
<tr>
<td>Bedroom</td>
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<td>0.0000</td>
<td>0.0525</td>
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<td>0.0000</td>
<td>-0.4111</td>
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</tr>
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<td>-0.0031</td>
</tr>
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<td>-3.93E-07</td>
</tr>
<tr>
<td>Property Age²</td>
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</tbody>
</table>
### Exhibit 6 (continued)

Regression Results After Excluding Transitory Data

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Traditional Approach</td>
<td>2SLS</td>
<td>2SLS-Heckman Model</td>
</tr>
<tr>
<td></td>
<td>Coeff.</td>
<td>P-value</td>
<td>Coeff.</td>
</tr>
<tr>
<td>Ownership Type</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fee-simple</td>
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<tr>
<td>Log(sales volume)</td>
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<td>0.1117</td>
</tr>
<tr>
<td>Summer</td>
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<td>0.1400</td>
<td>0.0062</td>
</tr>
<tr>
<td>Fall</td>
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</tr>
<tr>
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<td>0.028</td>
<td>0.0000</td>
<td>0.0902</td>
</tr>
<tr>
<td>2009</td>
<td>-0.001</td>
<td>0.9350</td>
<td>0.0615</td>
</tr>
<tr>
<td>2010</td>
<td>-0.119</td>
<td>0.0000</td>
<td>-0.0565</td>
</tr>
<tr>
<td>$R^2$</td>
<td>80.38%</td>
<td></td>
<td>80.40%</td>
</tr>
</tbody>
</table>

Notes: The base (omitted) class of some of the multi-class categorical variables are: “central” in cooling system, “condo” in ownership type, “Spring” in season and “2004” in year of sale. The number of observations in Model 1 is 123,669; the number of observations in Model 2 2SLS is 123,669; the number of observations in Model 2 2SLS-Heckman Model is 225,846 the number of observations in Model 2 2SLS is 102,177 for censored observations. The other control variables in all models are: floor type, heating system, waterfront descriptions, parking, and location at the ZIP Code level.
### Exhibit 7 | Regression Results for Attached Houses

<table>
<thead>
<tr>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traditional Approach</td>
<td>2SLS</td>
<td>2SLS-Heckman Model</td>
</tr>
<tr>
<td>Coeff.</td>
<td>P-value</td>
<td>Coeff.</td>
</tr>
<tr>
<td>Intercept</td>
<td>10.15</td>
<td>0.0000</td>
</tr>
<tr>
<td>Effect of TOM on selling price</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Down market</td>
<td>0.000307</td>
<td>0.0000</td>
</tr>
<tr>
<td>Up market</td>
<td>0.000793</td>
<td>0.0000</td>
</tr>
<tr>
<td>Property Characteristics</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Ownership Type</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Sales Volume, Season, and Year of Sale</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Location Controlled (ZIP Code level)</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>$R^2$</td>
<td>74.54%</td>
<td></td>
</tr>
</tbody>
</table>
### Exhibit 7 | (continued)
Regression Results for Attached Houses

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Traditional Approach</td>
<td>2SLS</td>
<td>2SLS-Heckman Model</td>
</tr>
<tr>
<td>Coeff.</td>
<td>P-value</td>
<td>Coeff.</td>
<td>P-value</td>
</tr>
<tr>
<td>Intercept</td>
<td>10.56</td>
<td>0.0000</td>
<td>12.11</td>
</tr>
<tr>
<td>Effect of TOM (days) on selling price</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Down market</td>
<td>0.000166</td>
<td>0.0000</td>
<td>-0.000142</td>
</tr>
<tr>
<td>Up market</td>
<td>0.000822</td>
<td>0.0000</td>
<td>0.000822</td>
</tr>
<tr>
<td>Property Characteristics</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Ownership Type</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Sales Volume, Season, and Year of Sale</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Location Controlled (ZIP Code level)</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>$R^2$</td>
<td>73.56%</td>
<td>73.57%</td>
<td></td>
</tr>
</tbody>
</table>

Notes: In Panel A, the number of observations in Model 1 is 58,829; the number of observations in Model 2 2SLS is 58,829; the number of observations in Model 2 2SLS-Heckman Model is 105,225; the number of observations in Model 2 2SLS is 46,396 for censored observations. In Panel B, the number of observations in Model 1 is 44,894; the number of observations in Model 2 2SLS is 44,894; the number of observations in Model 2 2SLS-Heckman Model is 79,410; the number of observations in Model 2 2SLS is 34,516 for censored observations.
Conclusion

Search is a fundamental characteristic of the real estate trading process, and the impact of search on selling price is a frequently studied subject in real estate research. Still, despite a large body of literature, empirical research remains divided as to whether the price–TOM correlation is positive or negative. Recent work by An, Cheng, Lin, and Liu (2013) attempts to settle the dispute by showing that the correlation need not be singular. Rather, they show the correlation can be anything—positive, negative, or insignificant—depending on the market conditions under which the properties are sold. We do not dwell on the “positive or negative” debate, as the answer appears to be “it depends on the market condition.” Instead, we focus on understanding how search can benefit investors in different market conditions. We argue that search affords investors the ability to influence selling price so that individual marketing efforts can offset the negative price trend of a declining market and compounds the positive price trend of a growing market. In other words, it reduces the downside risk and magnifies the upside potential for the seller making search beneficial under either market condition. This is an important advantage unavailable to investors in more efficient security markets where market participants are mere price-takers.

Using a large sample of properties in the Virginia Beach–Norfolk, Virginia metropolitan area during an extended period of time, we conduct a series of analyses to examine the impact of search (as indicated by TOM) on selling price during two distinctly separate up and down market cycles. We find that the effect of search on price, in terms of the magnitudes of the regression coefficients on TOM, is always greater in the up market than it is in the down market. That is, the effect is not symmetric. This is consistent with our intuition that search makes the seller better off in an up market and less worse off in a down market. In fact, our data indicate that even during the 2008–2011 period when the local housing market was continuously declining, the effect of search on price is still positive, suggesting the search effort more than offsets the negative market trend and the optimal selling strategy in such a declining market is to take the time to search as opposed to selling right away. This is different from the securities market where the optimal trading strategy is to sell as soon as possible to avoid further price decline. Certainly, our findings do not preempt the possibility where search is not enough to offset the impact of a greater market decline, in which case the price–TOM correlation will be negative. However, if the findings of An, Cheng, Lin, and Liu (2013) are of guidance, a negative TOM effect only occurs in extremely rapidly declining markets.

Endnotes

1 Intuitively, “longer selling time” must be of a reasonable duration in which the benefit of search justifies the cost. Beyond that, excessive search could send a negative signal and result in a lower selling price (Taylor, 1999).
Although Gwin (2004) suggests that real estate brokers tend to not disclose too much property information online out of fear of disintermediation, Hohenstatt, Kasbauer, and Schaffers (2011), among others, find evidence that the advances in Internet technology such as Google data help to improve the market efficiency and search effectiveness.

There are two other issues with the specification of Model 1. First, the fact that \( \text{TOM} \) and \( \text{MarketCondition} \) are included only as separate independent variables presumes that they are independent in reality, that is, \( \text{TOM} \) is not affected by market conditions. But the reality is that \( \text{TOM} \) is strongly influenced by market conditions. So assuming them to be independent is problematic. Second, because Model 1 can only estimate one coefficient \( \gamma \) for \( \text{TOM} \), it effectively presumes there can only be one type of relation between price and \( \text{TOM} \) regardless of market conditions, which precludes the possibility that the coefficient of \( \text{TOM} \) may take different signs given different market conditions. In other words, the regression coefficient \( \gamma \) obtained in Model 1 is effectively some kind of average of the impact of \( \text{TOM} \) on price under all market conditions that are controlled in the sample. As such, it does not indicate a relation under any particular market conditions.

For brevity, the estimated coefficients for the location control, 13 types of flooring, 26 types of heating systems, 22 types of parking arrangements, and 19 types of various waterfront and view features are not reported.

It should be noted that the linear interpretation is valid only within a reasonable range of \( \text{TOM} \), beyond which range the marginal benefit of waiting diminishes with \( \text{TOM} \) (Cheng, Lin, and Liu, 2008).

While attached homes are far more likely to be condos, and detached homes are fee-simples, there are some detached condos and attached fee-simples. To be sure, we also conducted a detached fee-simple-only homes analysis, but the results are virtually the same.

References


