UCF COLLEGE OF BUSINESS ADMINISTRATION

Dr. P. Phillips School of Real Estate

Housing Market Microstructure:

What Is a Competing House?

Geoffrey K. Turnbull
University of Central Florida
gturnbull@bus.ucf.edu

Velma Zahirovic-Herbert*
University of Georgia
vherbert@uga.edu

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Geoffrey K. Turnbull
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Velma Zahirovic-Herbert*
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vherbert@uga.edu

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Abstract. This paper tests alternative empirical housing microstructure models in which substitute houses are nearby houses on the market at the same time that have similar price or size. The empirical model of substitute houses matters, since conclusions regarding the strength of spatial competition and shopping externalities from surrounding houses vary significantly across specifications. While the non-nested specification tests do not indentify a single model that unilaterally dominates all others, the tests support a set of specifications that yield consistent implications for competition and shopping externality effects arising from nearby houses for sale.

JEL Subject Codes: R21, R31

Keywords: shopping externality, spatial competition, substitute house, house price

Geoffrey K. Turnbull, Dr. P. Phillips School of Real Estate and the Department of Finance, University of Central Florida, 4000 Central Florida Blvd., P.O. Box 161400, Orlando, FL 32816-1400; email: gturnbull@bus.ucf.edu

****Corresponding author*****:** Velma Zahirovic-Herbert, Department of Housing and Consumer Economics, University of Georgia, 205 Dawson Hall, 305 Sanford Drive, Athens, GA 30602; email: vherbert@uga.edu

1. Introduction

A greater number of sellers in a competitive market increases competition for buyers, putting downward pressure on price. At same time, however, buyers may be attracted to locations with a greater concentration of sellers in order to reduce their search costs of contacting a wider variety of sellers. This shopping externality by itself increases the probability of a successful match between a given seller and buyer and leads to higher selling prices. Increasing the number of sellers surrounding a given seller therefore produces possibly countervailing competition and shopping externality effects on price.

The competition and shopping externalities arising from surrounding sellers are also relevant in housing markets, which are quintessential search markets. While conditions in the aggregate market reflect the sum of potential buyers and sellers across all neighborhoods, competition and shopping externality effects within individual neighborhoods represent microstructure characteristics that are important determinants of property value (Turnbull and Dombrow 2006). Changes in the spatial distribution of buyers and sellers alter the relative balance of supply and demand within individual neighborhoods even when no changes are evident in the aggregate market; house value reflects these differences in neighborhood market conditions.[1]

An additional substitute house for sale in the neighborhood increases the competition among sellers for buyers including the neighborhood in their searches. At the same time, however, an additional house for sale may also create a shopping externality for nearby houses that are also for sale by increasing the number of potential buyers drawn to search in the

[1] See Goodman and Thibodeau (1998, 2003) and Turnbull and Dombrow (2006). Appraisers have long recognized the importance of market microstructure in property valuation, specifically in terms of decline or improvement in neighborhood market conditions.

neighborhood. If the competition effect dominates, then increasing the number of surrounding houses listed for sale will decrease selling price. If, on the other hand, the shopping externality effect dominates, then increasing surrounding listings will increase selling price. But while search theory tells us that neighborhood market conditions such as the number of surrounding listings of houses for sale can be important determinants of value, the theory by itself does not tell us how best to measure substitute or competing houses in the neighborhood. This remains an empirical question.

The literature offers several suggestions for measuring market microstructure. In a series of influential papers, Goodman and Thibodeau (1998, 2003) define substitute houses as those priced similarly in the market.[2] Turnbull and Dombrow (2006) take a different direction by defining substitute houses as nearby houses of similar size. Which definition is better remains an open question, complicated by the fact that there may be other reasonable criteria for determining whether or not a nearby house for sale is a competing house. Nonetheless, to date there has been no attempt to rigorously evaluate alternative models of neighborhood market conditions or determine whether the difference in the price-based and size-based measures even matters.

This paper examines alternative empirical models of neighborhood market conditions suggested by previous studies. It considers a series of alternative models based on relative house size and relative price as indicators of whether or not surrounding houses for sale are substitutes. The estimated models show that the difference between the various measures can be empirically important; conclusions regarding the strength of spatial competition and shopping externalities from surrounding houses vary across specifications. The non-nested specification tests do not

[2] Goodman and Thibodeau (1998, 2003) also draw on house characteristics to identify competing houses in a hierarchical approach.

indentify a single model that unilaterally dominates all others. The specification tests, however, can be used to evaluate conflicting estimates across models regarding competition or shopping externalities from nearby vacant houses relative to occupied houses; the results clearly support the conclusion that surrounding vacant houses have stronger shopping externalities than occupied houses.

The discussion is organized as follows. Section 2 explains the data and the alternative empirical market microstructure models in the context of a standard hedonic house price function. Section 3 provides the empirical estimates and the results of the specification test analysis. Section 4 concludes.

2. The Data and Variables

2.1 The data.

This study uses the Multiple Listing Service (MLS) data for broker-assisted transactions completed between October, 1984, and April, 2005, in East Baton Rouge Parish, Louisiana (parishes in Louisiana are equivalent to counties in other states). The parish represents the core of the four parish metropolitan area with a population ranging from approximately 530,000 to 610,000 during the sample period. We end the sample period three months before hurricane Katrina in order to avoid the housing market turmoil induced by the aftermath of the historic devastation of surrounding gulf coast communities, including nearby New Orleans. The sample period is two decades during which the local housing market experienced a downturn driven by a long deep regional recession in the oil based economy, followed by a steadily rising market.

The data cover detached single family houses transactions recorded in the Baton Rouge MLS. We apply several filters to systematically clean the data. We avoid the new subdivision pricing bias by excluding from our sample houses that are less than two years old since the prices of houses in new subdivisions can diverge from the broader market until the new development reaches a critical mass (Sirmans et al. 1997). MLS listings were published in bi-weekly books during most of the sample period, which means that newly listed houses did not appear in print for up to 14 days. We only consider houses with full market exposure and so exclude those that sell in fewer than 14 days. The 997 houses on the market more than 400 days appear to be outliers, and so are also dropped from the sample. Since preliminary analysis reveals that this market exhibits segmentation, we omit houses that sell for less than $40,000 or more than $320,000. In order to minimize apparent data errors, we also drop houses with unusually small or unusually large living area for the locale (less than 300 or greater than 4500 square feet) or unusual net area of utility rooms, covered porches, and carports (less than 110 and greater than 4000 square feet). The cleaned data set covers 27,936 transactions.

2.2 The base hedonic model.

Table 1 reports summary sample statistics for the variables used in the various empirical models. The log of sales price is the dependent variable in all models. The sales price (*Price*), number of bedrooms (*Bedrooms*), number of bathrooms (*Bathrooms*), the age of the house (*Age*), living area (*Living area*), and the number of fireplaces (*Fireplaces*) are drawn directly from MLS sales records. The *Net area* variable is the difference between the total square feet under roof less the square feet of living area.

All of the models include this set of variables as well as year and seasonal fixed effects and a complete set of census block dummy variables. Our location fixed effects approach is similar to Clapp et al. (2008) who use census tract fixed effects to control for omitted neighborhood characteristics. In this application, though, fixed effects are based on census block groups that are a very small geographic measure of the neighborhood; in some cases smaller than the geographic extent of single subdivisions in Baton Rouge. We use 265 fixed effects; the smallest census block group has only 36 observations and the largest 1,938 observations. Clapp et al. (2008) argue that such detailed fixed effects alone should be adequate to control for omitted neighborhood effects. Davis (2004) similarly points out that a fixed effects model with clustered errors provides a straightforward alternative to computationally cumbersome spatial lag frameworks (Davis 2004, Heintzelman 2010).[3]

Haurin (1988) and a large subsequent literature shows the importance of including in hedonic value models variables that control for differences in the mix of existing types of houses in the surrounding neighborhood whenever possible. Therefore all models include *Larger* and *Smaller* variables to pick up atypicality and size-related tax-service capitalization effects for houses that are larger or smaller than the average house in the neighborhood (Haurin 1988, Turnbull et al. 2006). To construct these variables, first index all houses within a one half mile radius of house *i* by *J* and then calculate the size of house *i* relative to the average in the surrounding neighborhood as[4]

$$Size_i = \frac{Living\ \ area_i - \sum_{j\in J} Living\ \ area_j \big/ N_J}{\sum_{j\in J} Living\ \ area_j / N_J}$$

[3] Additionally, Pace and LaSage (2010) conclude that the latter approach does not necessarily mitigate omitted variable bias.

[4] The set of neighboring houses is calculated using the set of houses that sold at least once during the 20 year sample period.

where N_J denotes the number of surrounding houses in the neighborhood J. Now define the variables $Larger_i$ and $Smaller_i$ as the absolute values of the positive and negative values of $Size_i$ to allow for asymmetric relative house size effects on value:

$$Larger_i = |Size_i| \text{ for } Size_i > 0$$
$$= 0 \text{ otherwise;}$$
$$Smaller_i = |Size_i| \text{ for } Size_i < 0$$
$$= 0 \text{ otherwise.}$$

Note when interpreting coefficient estimates that these variables are continuous variables and both are non-negative by construction. This approach is sufficiently flexible to allow for the types of asymmetric relative size effects on value implied by capitalization theory (Turnbull et al. 2006).

The *Vacant* dummy variable indicates vacant property. When controls for spatial competition/shopping externalities and relative size are included in the model, we expect the *Vacant* coefficient primarily to pick up the net effects of higher seller holding costs and lower seller bargaining power associated with empty houses (Harding et al. 2003, Turnbull and Zahirovic-Herbert 2011).

The *Rental* dummy variable indicates a tenant occupied house. Existing studies indicate that rental houses sell at a discount, in part reflecting the rental externality and possibly the difficulty of showing rental houses to buyers in their best light due to restricted showing times or tenants' housekeeping habits (Shilling et al. 1991, Springer 1996, Munneke and Slawson 1999, Harding et al. 2003, Clauretie and Wolverton 2006, Turnbull and Zahirovic-Herbert 2010).

2.3 Measuring neighborhood market conditions.

All of the extended hedonic price models include the set of base model variables plus market microstructure variables measuring neighborhood market conditions by the number of nearby substitute houses for sale at the same time. The alternative neighborhood market conditions variables differ only in how they define houses that are substitutes for the house under examination (to be defined shortly), but the general form is as follows. Regardless of whether defined as a competing house in terms of similar size, price, or configuration, a substitute or competing house *j* in the neighborhood must be on the market during a period overlapping with the period that house *i* is on the market. Each such overlapping listing *j* is weighted by a nonlinear function of the distance between the houses *i* and *j* so that nearby houses have a stronger influence on selling price than those farther away. If *l(i)* and *s(i)* are the listing date and sales date for house *i*, respectively, then the days-on-market or selling time for house *i* is $s(i)-l(i)+1$. The overlapping time on the market for the alternative house *j* with house *i* is $\min[s(i), s(j)] - \max[l(i), l(j)] + 1$. The straight-line distance in miles between houses *i* and *j* is *D(i,j).* The basic formula for calculating *Listing Density*, the number of substitute house listings in the neighborhood of house *i* per day that house *i* is on the market is

$$Listing \quad Density(i) = \sum \frac{(1 - D(i,j))^2 \left\{ \min\left[s(i), s(j) \right] - \max\left[l(i), l(j) \right] \right\}}{s(i) - l(i) + 1}$$

Each of the alternatives spelled out below defines substitute houses as those within one mile of house *i.* We use the STATA algorithm provided by Zahirovic-Herbert (2008) to construct this variable using all applicable competing house sales, which include all relevant competing houses listed before and after the estimation period, January 1985 to March 2005, that overlap with the listing period for each house sold in the sample.[5]

Turnbull and Dombrow (2006) use a simple search model to show that competition from neighboring houses on the market reduces buyer willingness to pay for a given house and dilutes the likelihood that buyers will include the house in their search within the neighborhood; both effects depress expected selling price. At the same time, however, shopping externalities from neighboring houses on the market increase the likelihood that buyers will include the house in their search within the neighborhood, which increases expected selling price. The *Listing Density* coefficient in the hedonic price function picks up the net effects of competition and shopping externalities from substitute houses in the neighborhood. Competition by itself leads to negative coefficients; zero or positive coefficients indicate the presence of shopping externalities.[6]

Potential buyers may view vacant houses for sale in the neighborhood as a different degree of substitute than an otherwise identical occupied house. Similarly, newly listed houses (those within 14 days of listing on the MLS) may have different shopping externality and competition effects than houses that have been on the market longer.[7] To allow for possible differential selling price effects, the expanded models in this paper also include *Vacant Density* and *New Density* variables, which are listing density measures for neighboring vacant and newly listed houses, respectively. The coefficients on these variables capture any add-on or additional competition or shopping externality effects associated with vacant or newly listed surrounding houses. Positive coefficients on these variables indicate stronger shopping externality effects

[5] The burn-in and burn-out periods at the beginning and end of the sample used in the estimation are required in order to correctly identify all houses that overlap on the market with each house in the estimation sample.

[6] A negative *Listing Density* coefficient does not imply zero shopping externality effects. Rather, it implies that shopping externalities—if present—are weaker than competition effects from surrounding houses. See Turnbull and Dombrow (2006) for derivation of the results summarized in this paragraph and further explanation.

[7] Recall that houses sold within 14 days do not have full market exposure for the majority of our sample period and so the sales of such houses are not included in the hedonic price function sample. Nonetheless, they are included in the calculation of overlapping neighborhood listings for the transactions in our sample.

than occupied or longer term listings; negative coefficients indicate stronger competition effects; and insignificant coefficients indicate no difference in competition or shopping externality effects between these types of houses and occupied or longer term listings.

2.4 Alternative substitute house models.

The central question is, which houses should be included in the set of substitutes for house *i* when constructing the various listing density variables? To answer this question, we consider different empirical models of what constitutes a substitute house. The alternatives are defined as follows.

The literature offers two different empirical definitions for substitute houses: houses of similar size (Turnbull and Dombrow 2006) and houses with similar prices (Goodman and Thibodeau 1998, 2003). We consider two size-based *Listing Density* variables. The first, *Listing Density* (*Area*) follows the measure adopted by Turnbull and Dombrow (2006) and a handful of subsequent studies, defining substitute houses as those within one mile of *i* with overlapping time on the market and living area within 20 percent of the living area of house *i*. Table 2 reveals that there are about 2.5 such competing houses each day the average house is on the market, but this measure of neighborhood competition exhibits wide variation across observations, ranging from zero to over 20.

The second size-based area definition of substitute houses is motivated in part by the fact that a reliable measure of living area is not always readily available in standard transactions data. (In some states, listing services do not identify living area in order to mitigate potential liability for errors). In such cases, however, other measures such as number of bedrooms are available. Therefore, *Listing Density* (*Bedrooms*) defines houses with the same or one more bedroom as substitutes for house *i*. This version assumes that it is easier for potential buyers to adapt to more rather than to fewer bedrooms. For *Listing Density* (*Bedrooms*), the average number of competing houses by this measure for each day a house is on the market is slightly over 3.5 and ranges from zero to slightly less than 20.

We also consider two alternative price-based definitions of substitute houses motivated by the rationale offered by Goodman and Thibodeau (1998, 2003). The first, *Listing Density (Sell Price)* considers all houses within one mile that are on the market at the same time as *i* (i.e., whose listing periods overlap with the subject house) and that eventually sell for prices within 20 percent of the price of house *i*. The second, *Listing Density (Ask Price)* is similarly defined, except that substitute houses are those with asking or listing prices within 20 percent of the subject house *i*. The sample statistics for these two alternative market microstructure measures are very similar, with means of about 2.3 and values ranging from zero to around 18.

Finally, as reported in tables 5 and 6, the extended models (3), (5), (7), and (9) include appropriately defined *Vacant Density* and *New Density* variables as additional explanatory variables. The substitute house definition underlying the construction of each of these variables follows the alternative definitions explained above.

3. Comparing the Alternative Substitute House Models

Table 3 reports the correlation coefficients among neighborhood market conditions measures based on different definitions of substitute houses. The correlations for the various *Listing Density* variables constructed using living area and selling price, living area and asking price, and selling price and asking price generally exceed 0.80. Many of the other measures, though, exhibit relatively low correlations. It appears that many of the variables based on alternative substitute house definitions, while correlated, may be picking up different aspects of neighborhood market conditions. This raises the question whether the empirical conclusions vary across specifications, the starting point of our analysis.

3.1 Estimates of the alternative models.

Table 4 reports parameter estimates for the base hedonic model with no spatial competition or shopping externality controls (the model includes time and location fixed effects, but they are not reported); all of the other models in this study also include these variables, although, for brevity, complete coefficient estimates are not reported in later tables. The dependent variable in all cases is the log of selling price. There is nothing surprising in these estimates. Although not reported in later tables, we note that all of the estimates for the base model variables are remarkably robust across all of the formulations considered in this paper. In this regard, at least, the different specifications of the market microstructure variables do not appear to matter.

Nonetheless, the conclusions regarding neighborhood market conditions effects on selling price do vary across models. For example, the simplest versions that add only the appropriately defined *Listing Density* variable to the base variables exhibit significantly different estimates that yield conflicting conclusions about competition and shopping externality effects from surrounding properties. Looking at model (2) in table 5, the *Listing Density* (*Area*) coefficient is not significant. Nor is the *Listing Density* (*Bedrooms*) in model (4) in table 5 or the *Listing Density* (*Sell Price*) in model (6) in table 6 at the 1% level. These estimates are consistent with the presence of offsetting competition and shopping externalities from surrounding houses for sale. In contrast with these estimates, the *Listing Density* (*Ask Price*) has a significantly negative coefficient in model (8) in table 6, indicating a weak or possibly nonexistent shopping externality effect when using this definition of substitute houses in the neighborhood.

The other extended models in tables 5 and 6 include the complete set of controls for neighborhood market conditions, the appropriately defined *Listing Density* along with the *New Density*, and *Vacant Density* variables. What is interesting here is that the differences in *Listing Density* estimates across models observed earlier disappear. But other differences arise. Looking again at table 5, the *Listing Density* (*Area*) is now significantly positive in model (3), indicating a strong shopping externality effect while the *New Density* (*Area*) and *Vacant Density* (*Area*) are significantly negative and positive, respectively. This pattern suggests stronger competition effects of nearby new listings and stronger shopping externalities from nearby vacant listings than from other surrounding houses for sale. This same pattern is evident for the selling price and listing price based models (7) and (9) in table 6, but not the bedroom based model (5) in table 5. In model (5) the *Listing Density* (*Bedrooms*) and *New Density* (*Bedrooms*) show the same pattern as in the other models, but *Vacant Density* (*Bedrooms*) is not significantly different from zero. Model (5) implies that surrounding vacant houses have no incremental competition or shopping externality effects not already found in other properties.

In summary, three of the four models tested yield identical conclusions about how occupied, newly listed, and vacant houses in the neighborhood affect price. While three out of four models yielding similar results might seem encouraging, it does not provide a sufficiently rigorous basis for evaluating these conclusions with the contrasting results from the remaining model. Put differently: given the difference in conclusions across the alternative models, the question remains, in which model (hence conclusions) do we have the most confidence? That is, when sufficient data is available to compute the various alternative measures of neighborhood market condition, which is the most appropriate? The next sub-section directly addresses this question.

3.2 Non-nested specification tests.

Models including measures of neighboring new and vacant listings dominate the simpler versions without those controls: straightforward application of *F*-tests reject the simplest model (2) in favor of model (3) including separate measures of surrounding new listings and vacant listings, model (4) in favor of model (5), etc. This much is straightforward.

But how do we evaluate the alternative substitute house definitions themselves? Each model (3), (5), (7), and (9) is an alternative that is not nested within any of the others; that is, the model with living area based neighborhood market conditions variables cannot be derived as a special case of any of the other models and vice versa. Goodness-of-fit tests like maximizing adjusted R^2 are not appropriate for evaluating such non-nested models. In any case, there is not sufficient variation in the adjusted R^2 across the alternative models to make such a choice feasible. So we turn to tests designed to evaluate such non-nested hypotheses, the Atkinson *J*-test (Atkinson 1970). The test yields an asymptotically normal distributed statistic that can be used to compare pair-wise mutually exclusive non-nested models. Each model takes the role of the maintained or null hypothesis, with the other taking the role of the alternative hypothesis. Then the roles are reversed in order to complete the bilateral test. The test results can indicate bilateral acceptance (cannot reject either model), unilateral rejection (reject one model and not the other), and bilateral rejection (both models are equally poor performers).

These tests evaluate the performance of each specification against the others in the set of tested models while at the same time testing the performance of each specification against unspecified (unknown) alternative hypothetical models not yet identified. As a result, Pesaran (1974) argues that such tests will often indicate rejection of all of the tested specifications in most economic applications. Still, the tests can yield useful information. Turnbull and Djoundourian (1994) argue that this type of test can identify the specification with the strongest statistical support among the tested (known) models as that which is rejected by the fewest alternatives in the set of tested models.

Table 7 reports the *J* statistics for each of the pair-wise tests. The models listed along the first column take the role of the maintained hypothesis and the models listed along the top row take the role of the alternative hypothesis. According to these results, the area based definition (3), the bedroom based definition (5) and the selling price based definition (7) of substitute houses are each rejected against all others. Only the list price based definition of substitute houses (9) receives some support from the *J* test; this model is rejected against models (3) and (7), but not against the bedroom based model (5).

Overall, the *J* test does not provide unambiguous support for any one of the models against all others, the usual result anticipated by Pesaran (1974). The list price based definition of substitute houses (9) performs better than the others according to the Turnbull-Djoundourian criterion, but only modestly so. While we choose to interpret the results reported in this table as providing some support for the listing price definition of substitute houses over the other alternatives, it is nonetheless reasonable to conclude instead that all of the models are equivalent in this regard. But even in this case, the *J* test still provides guidance in model selection as demonstrated in the following.

Since a non-negative coefficient on the neighborhood market condition variable implies the presence of shopping externalities, all of the models provide evidence of some shopping externality effects from surrounding substitute houses, although the living area and bedroom based models indicate stronger shopping externalities than do the selling price and list price based models. And all of the models also show that neighboring newly listed houses have stronger competition effects than houses with full exposure to the market. The models differ, however, for vacant house effects. Vacant houses exhibit significantly stronger shopping externality effects than occupied houses in the area, selling price, and listing price based models of substitute houses while vacant houses exhibit no significant incremental competition or shopping externality effects in the bedroom based model. Here, however, we can draw on the *J* test which unilaterally rejects the bedroom based model (5) in favor of the list price based model (9); applied this way, the *J* test rejects the conclusion that vacant houses have no incremental shopping externality or competition effects in favor of the conclusion that vacant houses have significantly stronger shopping externality effects than other nearby houses.

4. Conclusion

The housing market microstructure literature emphasizes the importance of neighborhood market conditions in determining house prices and liquidity. There has been no attempt to evaluate the different empirical approaches taken in the literature; this paper offers the first empirical evaluation of alternative approaches. One approach identifies substitute houses as those with similar prices, either selling or listing prices. Another approach identifies substitute houses as those with similar sizes, measured either by living area or number of bedrooms. In all cases the neighborhood market conditions have meaningful effects on sales prices. But the choice of model matters—the qualitative implications of microstructure in terms of competition or shopping externalities effects on house price vary across the different formulations.

The non-nested specification test does not provide unequivocal support for any single model of neighborhood market conditions over all alternatives (including unknown alternatives not explicitly tested), which we argue is not an unusual outcome in economic empirical modeling. While there is modest support for defining substitute houses in terms of listing price, we can also justify defining substitute houses in terms of similar living area or ultimate selling price but not in terms of number of bedrooms.

More generally, the non-nested specification tests provide a means of resolving conflicting model implications. In particular, all of the models provide evidence of some shopping externality effects from surrounding substitute houses, but three of the four tested models find that vacant houses have significantly stronger shopping externality effects than occupied houses while one model does not. The specification test clearly rejects the one substitute house model that finds no vacant house shopping externality in favor of one of the others that find a significant incremental shopping externality for vacant houses.

References

Arnott, R. 1989. Housing Vacancies, Thin Markets, and Idiosyncratic Tastes. *Journal of Real Estate Finance and Economics,* 2: 5-30.

Atkinson, A.C. 1970. A Method for Discriminating Between Models. *Journal of the Royal Statistical Society, Series B*, vol. 32, 323-53.

Clapp, J., A. Nada, and S.L. Ross. 2008. Which School Attributes Matter? The Influence of School District Performance and Demographic Composition on House Values. *Journal of Urban Economics* 63: 451-466.

Clauretie, T. M. and Wolverton, M.L. 2006. Vacant or Rent: The Optimal Decision for Absentee Home Sellers. *Journal of Real Estate Research*, 28: 25-38.

Davis, L. 2004. The Effect of Health Risk on House Values: Evidence from a Cancer Cluster. *American Economic Review* 94: 1693-1704.

Goodman, A., and T. Thibodeau. 1998. Housing Market Segmentation. *Journal of Housing Economics 7*: 121-143.

Goodman, A., and T. Thibodeau. 2003. Housing Market Segmentation and Hedonic Prediction Accuracy. *Journal of Housing Economics 12*: 181-201.

Harding, J.P., J.R. Knight and C.F. Sirmans. 2003. Estimating Bargaining Effects in Hedonic Models: Evidence from the Housing Market. *Real Estate Economics* 31: 601-622.

Haurin, D. 1988. The Duration of Marketing Time of Residential Housing. *AREUEA Journal* 16: 396-410.

Haurin, D.R., J.L. Haurin, T. Nadauld and A. Sanders. 2010. List Prices, Sales Prices and Marketing Time: An Application to the U.S. Housing Market. *Real Estate Economics* 38: 659-686.

Hintzelman, M. D. 2010. Measuring the Property-value Effects of Local Land use and Preservation Referenda. *Land Economics* 68: 22-47.

Iwata, S. and H. Yamaga. 2008. Rental Externality, Tenure Security, and Housing Quality. *Journal of Housing Economics* 17: 201-211.

Knight, J.R. 2002. Listing Price, Time on the Market, and Ultimate Selling Price: Causes and Effects of Listing Price Changes. *Real Estate Economics* 30: 213-237.

Knight, J.R., C.F. Sirmans and G. K. Turnbull. 1994. List Price Signaling and Buyer Behavior in the Housing Market. *Journal of Real Estate Finance and Economics* 9: 177-192.

Munneke, H.J. and V.C. Slawson, Jr. 1999. A Housing Price Model with Endogenous Externality Location: A Study of Mobile Home Parks. *Journal of Real Estate Finance and Economics* 19: 113-131.

Pace, K. R. and J. P. LeSage. 2010. Omitted Variable Biases of OLS and Spatial Lag Models, In: A. Paez, J. Le Gallo, R. N. Buliung, and S. Dall'erba (eds.), Progress in Spatial Analysis: Methods and Applications, Springer, pp. 17-28.

Pesaran, M.H. 1974. On the General Problem of Model Selection. *Review of Econometric Studies*, 41: 153-171.

Shilling, J. D., C. F. Sirmans, and J. Dombrow. 1991. Measuring Depreciation in Single-Family Rental and Owner-Occupied Housing. *Journal of Housing Economics* 1: 368-383.

Sirmans, C.F., G.K. Turnbull and J. Dombrow. 1997. Residential Development, Risk, and Land Prices. *Journal of Regional Science* 37: 613-628.

Turnbull, G.K. and J. Dombrow. 2006. Spatial Competition and Shopping Externalities: Evidence from the Housing Market. *Journal of Real Estate Finance and Economics* 32: 391-408.

Turnbull, G.K., J. Dombrow and C.F. Sirmans. 2006. Big House, Little House: Relative Size and Value. *Real Estate Economics* 34: 439-456.

Turnbull, G.K. and S. Djoundourian. 1994. The Median Voter Hypothesis: Evidence from General Purpose Local Governments. *Public Choice* 81: 223-240.

Turnbull G.K. and C.F. Sirmans. 1993. Information, Search, and House Prices. *Regional Science and Urban Economic* 23:545–557

Turnbull, G.K. and V. Zahirovic-Herbert. 2010. The Transitory and Legacy Effects of the Rental Externality on House Price and Liquidity. *Journal of Real Estate Finance and Economics* forthcoming. doi: 10.1007/s11146-010-9235-6.

Turnbull, G.K. and V. Zahirovic-Herbert. 2011. Why Do Vacant Houses Sell for Less: Bargaining Power, Holding Cost or Stigma? *Real Estate Economics* 39: 19-43.

Wheaton, W. 1990. Vacancy, Search, and Prices in a Housing Market Matching Model. *Journal of Political Economy* 98: 1270-1292.

Wu C and P.F. Colwell. 1986 Equilibrium of Housing and Real Estate Brokerage Markets under Uncertainty. *AREUEA Journal* 14:1–23

Yavas A. 1992. A Simple Search and Bargaining Model of Real Estate Markets. *AREUEA Journal* 20:533– 548

Yavas, A. and Yang, S. 1995. The Strategic Role of Listing Price in Marketing Real Estate: Theory and Evidence. *Real Estate Economics* 23: 347-368.

Zahirovic-Herbert, V. 2008. A STATA Program for Localized Housing Market Conditions. Available at SSRN: http://ssrn.com/abstract=1676839

Table 1: Summary sample statistics house attribute variables, excluding location, time and seasonal fixed effects.

Variable	***Description***	***Obs***	***Mean***	***Std. Dev.***	***Min***	***Max***
Dependant Variable						
Price	Selling price of house	27936	112473.3	53425.55	40000	320000
House Attributes						
Bedrooms	Number of bedrooms	27936	3.332224	0.6064988	1	7
Bathrooms	Number of bathrooms	27936	2.02495	0.4790813	1	7
Age	Age of the structure	27936	21.03279	16.08394	2	100
Living area	Square feet of living area	27936	1947.429	589.6199	359	4493
Fireplace	Number of fireplaces	27936	0.6819874	0.531613	0	3
Net area	Area under roof less living area	27936	707.4799	318.7984	110	3925
Age_sq	Age square	27936	701.0621	1137.227	4	10000
Living area_sq	Living area square	27936	4140119	2667175	128881	20200000
Net area_sq	Net area square	27936	602156.6	638679.8	12100	15400000
Smaller	Negative deviation from local mean living area	27936	0.0693188	0.1040621	0	0.8882827
Larger	Positive deviation from local mean living area	27936	0.1083341	0.1882156	0	2.058043
Vacant	Vacant house dummy variable	27936	0.2992554	0.4579401	0	1
Rental	Rental house dummy variable	27936	.0450673	.2074555	0	1

Table 2: Summary sample statistics for market microstructure variables.

Variable	*Description*	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
Area-based Measures						
Listing Density (Area)	Area-based competing listings per day on market	27936	2.534616	2.127251	0	20.14701
New Density (Area)	New competing listings per day on market	27936	2.192691	1.643526	0	14.75921
Vacant Density (Area)	Vacant competing listings per day on market	27936	2.097592	1.685401	0	16.94644
Listing Density (Bedrooms)	Bedrooms-based competing listings per day on market	27936	3.55638	2.65676	0	19.89307
New Density (Bedrooms)	New competing listings per day on market	27936	1.594126	1.417566	0	13.84825
Vacant Density (Bedrooms)	Vacant competing listings per day on market	27936	1.5149	1.471449	0	16.94644
Price-based Measures						
Listing Density (Sell Price)	Selling Price-based competing listings per day on market	27936	2.287653	1.914284	0	18.27889
New Density (Sell Price)	New competing listings per day on market	27936	1.060846	1.049756	0	9.717745
Vacant Density (Sell Price)	Vacant competing listings per day on market	27936	0.9176548	1.023637	0	12.81916
Listing Density (Ask Price)	Asking Price-based competing listings per day on market	27936	2.297297	1.926794	0	17.64612
New Density (Ask Price)	New competing listings per day on market	27936	1.06601	1.058953	0	9.912617
Vacant Density (Ask Price)	Vacant competing listings per day on market	27936	0.9294778	1.039277	0	12.57585

Table 3: Correlation matrix for alternative market microstructure *Listing Density* measures.

	Listing Density	***New Density***	***Vacant Density***	***Listing Density (Bedrooms)***	***New Density (Bedrooms)***	***Vacant Density (Bedrooms)***	***Listing Density (Sell Price)***	***New Density (Sell Price)***	***Vacant Density (Sell Price)***	***Listing Density (Ask Price)***	***New Density (Ask Price)***	***Vacant Density (Ask Price)***
Listing Density(Area)	1.00											
New Density(Area)	0.61	1.00										
Vacant Density(Area)	0.66	0.59	1.00									
Listing Density (Bedrooms)	0.75	0.62	0.68	1.00								
New Density (Bedrooms)	0.59	0.85	0.50	0.79	1.00							
Vacant Density (Bedrooms)	0.64	0.49	0.86	0.83	0.62	1.00						
Listing Density (Sell Price)	0.83	0.58	0.56	0.69	0.56	0.53	1.00					
New Density (Sell Price)	0.65	0.78	0.41	0.54	0.73	0.39	0.79	1.00				
Vacant Density (Sell Price)	0.65	0.43	0.72	0.54	0.41	0.67	0.77	0.57	1.00			
Listing Density (Ask Price)	0.84	0.58	0.57	0.70	0.56	0.54	0.98	0.77	0.76	1.00		
New Density (Ask Price)	0.66	0.78	0.42	0.55	0.74	0.40	0.77	0.97	0.56	0.79	1.00	
Vacant Density (Ask Price)	0.66	0.43	0.72	0.54	0.41	0.67	0.75	0.56	0.96	0.78	0.57	1.00

Table 4: Baseline model hedonic house price regression estimates

	Base model
	(1)
House Attributes	
Bedrooms	-0.0179***
	(0.00253)
Bathrooms	0.0295***
	(0.00343)
Age	-0.0143***
	(0.000242)
Living area	0.000963***
	(1.52e-05)
Fireplace	0.0210***
	(0.00239)
Net area	0.000176***
	(1.51e-05)
Age_sq	0.000145***
	(3.10e-06)
Living area_sq	-7.77e-08***
	(3.04e-09)
Net area_sq	-3.44e-08***
	(8.63e-09)
Vacant	-0.0639***
	(0.00207)
Rental	-0.0801***
	(0.00486)
Spring	0.00270
	(0.00258)
Summer	0.0125***
	(0.00256)
Fall	0.0155***
	(0.00272)
Smaller	0.482***
	(0.0173)
Larger	-0.399***
	(0.0130)
Constant	10.60***
	(0.0243)
Observations	27,936
Adj. R-squared	0.889

Dependent variable is ln(*Price).*
Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Year and location fixed effects estimates not reported here.

Table 5: Key parameter estimates for hedonic price models with area-based market microstructure variables.

	Models with area-based density measures			
	(2)	(3)	(4)	(5)
Local market conditions				
Listing Density (Area)	0.000514	0.00272***		
	(0.000466)	(0.000682)		
New Density (Area)		-0.00657***		
		(0.000741)		
Vacant Density (Area)		0.00143*		
		(0.000801)		
Listing Density (Bedrooms)			-0.000841**	0.00178**
			(0.000405)	(0.000764)
New Density (Bedrooms)				-0.00739***
				(0.000939)
Vacant Density (Bedrooms)				0.000804
				(0.00101)
Constant	10.60***	10.60***	10.61***	10.61***
	(0.0243)	(0.0243)	(0.0246)	(0.0246)
Observations	27,936	27,936	27,936	27,936
Adj. R-squared	0.889	0.889	0.889	0.889

Dependent variable is ln(*Price*).
Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Coefficients for house attributes and location, year and season fixed effects not reported here.

Table 6: Key parameter estimates for hedonic price models with price-based market microstructure measures.

	Models with price-based density measures			
	(6)	(7)	(8)	(9)
Local market conditions				
Listing Density (Sell Price)	-0.000882*	0.00110		
	(0.000514)	(0.000878)		
New Density (Sell Price)		-0.00952***		
		(0.00112)		
Vacant Density (Sell Price)		0.00467***		
		(0.00121)		
Listing Density (Ask Price)			-0.00167***	0.000617
			(0.000513)	(0.000889)
New Density (Ask Price)				-0.0104***
				(0.00112)
Vacant Density (Ask Price)				0.00478***
				(0.00121)
Constant	10.60***	10.60***	10.61***	10.61***
	(0.0243)	(0.0243)	(0.0243)	(0.0243)
Observations	27,936	27,936	27,936	27,936
R-squared	0.889	0.889	0.889	0.889

Dependent variable is ln(*Price).*
Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
Coefficients for house attributes and location, year and season fixed effects not reported here.

Table 7: Non-nested hypothesis test statistics.

		Alternative Hypothesis			
		(3)	(5)	(7)	(9)
Maintained Hypothesis	(3)		*J* = 4.33917 (0.00001)	*J* = 5.31283 (0.00000)	*J* = 6.50986 (0.00000)
	(5)	*J* = 10.87979 (0.00000)		*J* = 3.88004 (0.00010)	*J* = 5.42602 (0.00000)
	(7)	*J* = 11.01610 (0.00000)	*J* = 2.66546 (0.00769)		*J* = 5.31069 (0.00000)
	(9)	*J* = 10.75482 (0.00000)	*J* = 1.31470 (0.18862)	*J* = -2.26160 (0.02373)	

For each null hypothesis at the left, the top number in the row is the *J*-test statistic (with the p-value in parenthesis) for the alternate hypothesis at the head of the column.