In Search of Value: How Subdivision Names Influence House Prices and Marketing Duration

(preliminary--do not quote without author's permission)

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Abstract

The identity of residential areas has a strong influence on consumers searching for new housing. Yet, most studies have not dealt adequately with the implications of neighborhood name and characteristics as a marketing tool. This paper investigates how subdivision names selected by residential developers in Baton Rouge, LA impact property values and time on the market. We use a 20 year data series on house transactions to estimate these effects in a simultaneous model of price and marketing duration.

Keywords: house price, marketing duration, subdivision names.

Introduction

As newly constructed houses become more homogenous and markets more competitive, developers and sellers seek ways to enhance the positioning of properties against the developments of their competitors. While the science of developing brand strategies, as well as analyzing the effects of branding, is highly developed with regard to everyday and frequently purchased consumer items, there is less evidence of an empirical approach to brand names of the largest consumer product most people purchase: a house.

In general, naming products can be a complex task, and sophisticated analysis is required to understand the contribution of such names to the brand equity construct. Previous research has shown that choosing a name for a consumer product or service is critical in a homogenous market, and it is one of the most important decisions in the marketing process[1]. It is, therefore, expected that in a highly competitive environment residential developers would pay attention to naming as a key in their competitive brand strategies. However, while there is extensive literature available on the use and appeal of brand names for various goods and services[2], few previous studies have looked at the effect of naming strategies in residential property development[3].

A product name can enhance the appeal of a product to consumers as they may form inferential beliefs based on this characteristic. From the perspective of a consumer, a

[1] Landler, M. What's in a name?: less and less. Business Week (July 1991), 66-67.
[2] Collins, L. A name to conjure with: a discussion of the naming of new brands. European Journal of Marketing, (1997), 11(5), 340-363
[3] Ibrahim. M. and Leonard F. Naming Strategies of Residential Developments: Is there a Winning Formula?. Unpublished Research Project, Department of Real Estate, National University of Singapore. (April, 2009)

subdivision name can provide a symbolic cue and play a role in their decision making process.[4] Furthermore, research suggests that consumers prefer certain types of names that convey the desired attributes of the product of their interest. For example, successful geographic brand names associated with real estate properties should include locational references, such as descriptions of "place" and "land". Words related to the name of the local area, state or nation are used in some cases to provide a loyal or patriotic appeal.

Another study finds that consumers are willing to pay a premium on goods that can reduce their search costs. As a result, when a developer is able, through a product name, to convey some of the attributes that the consumers are looking for, it helps reduce the search cost for the consumers and increases their willingness to pay a premium. Evidence from experimental psychology finds that product names can help consumers reduce the time they may take to make their purchase decision. Additionally, a product or brand name helps project a desirable image of the product for consumers. An intangible benefit of creating this desirable image through a product name is that it also helps consumers build a sense of their belonging to a social group that they value and desire to be part off.

Therefore, appropriately named residential properties help provide information regarding the status and the environment of houses in a subdivision to the consumers. Because some aspects of the quality and benefits of a house or a residential property are not understood until it is owned for some time, consumers might rely on property names as a heuristic for quality when deciding which house to buy. The image of a residential

[4] Pavia, T. and Costa, J. The Winning Number: Consumer Perceptions of Alpha-Numeric Brand Names. Journal of Marketing, (October 1993), 85-98

property conveyed through its name is also expected to affect demand for it and selling price.

This paper studies whether names of residential developments drive the selling price and demand for residential properties, and whether they affect the duration for which these properties remain in the market. We investigate these issues using a unique dataset that allows us to measure the effect of strategies adopted by residential developers in Baton Rouge, LA.

The rest of this paper is organized as follows. Section 2 presents a simple empirical framework. Section 3 details the description of data and construction of the control variables. Section 4 offers an explanation of the empirical results for the 20 year sample. Section 5 concludes.

2. Empirical Model

Housing is a heterogeneous good that is spatially distinct. Buyers and sellers must expend resources to find potential matches and complete a transaction. Thus, in addition to pricing, the time component of the search process, or liquidity, is also relevant. Liquidity is usually defined as an asset characteristic that reflects how quickly the asset can be sold at a given price. In essence, the price-setting problem is an exercise in how to balance the desire to sell at a high price with the reality that high priced houses are likely to stay on the market for a long time. Thus, a common measure of liquidity is the marketing time under optimal pricing, or time-on-market (TOM).

The literature concerning the contribution of house characteristics or locational attributes to marketing time can be broken down into theoretical and empirical studies. The observation that exchange in the housing market takes place only after agents conduct a search suggests that it is possible to borrow models developed in other areas of economics, such as labor economics, to study asset pricing. The challenge arises in empirical studies because search and matching models of the housing market envision price and selling time as jointly determined outcomes so that different market or property characteristics typically lead to combined price and liquidity effects. This argues for taking into account simultaneous selling time or liquidity effects when conducting empirical hedonic price analysis. A fundamental econometric problem arises, however, because the theory implies that both price and liquidity are simultaneously determined by identical factors; the equations describing price and liquidity are an under-identified simultaneous system. Various aspects of the market environment, including both economic market factors and property characteristics, affect the marketing time as well as selling prices. For example, age of the structure sometimes acts as a proxy for housing condition; as a house ages, it deteriorates physically. Additionally, a house's design might be outdated, and the demand for such a house is likely to be reduced. It is anticipated that the marketing time for older houses would be longer. Similarly, higher selling prices are anticipated for Spring and Summer sales. Furthermore, it is shown that seasonality affects the marketing time in the residential real estate market. Consequently, technical problems arise because the specifications of both the price and TOM models are similar.

This paper uses the model of joint determination of house prices and marketing time.[5] The intuition behind their model can be summarized as follows. In the basic search theory for matching buyers and sellers, the house price and house marketing time are jointly determined by the same set of exogenous variables. Furthermore, a seller's choice of a reservation price determines both the expected selling price and the marketing time. The key insight developed in their model is that this complexity can be described as a standard constrained utility maximization problem. Basically, the distribution of buyers (and their associated willingness to pay) and the characteristics of the property determine the "budget constraint". The utility maximization problem requires the seller to tradeoff the price and holding costs associated with TOM. Under the assumptions underlying the model, the price and TOM equations can be estimated using SUR without ad hoc identifying restrictions on the model coefficients.

The empirical framework used in this study therefore follows the structure implied by applied consumer demand theory. Just as the utility maximization model in consumer theory yields the consumer's demands for two goods Y and Z as functions of the same predetermined variables (consumer preferences, prices of Y and Z, and income), our seller utility maximization model yields the seller's choice of expected selling price and marketing time as functions of the same set of predetermined variables (seller preferences, property characteristics, and market conditions—the last of which also reflects buyers' preferences, etc.). Because the mathematical structure of this problem is parallel to the consumer's problem in demand theory that yields demand equations that

[5] The model is originally developed in Turnbull, G.K., and V. Zahirovic-Herbert. "The Transitory and Legacy Effects of the Rental Externality on House Price and Liquidity" Journal of Real Estate Finance and Economics, forthcoming.

are functions of the same predetermined variables, the price and marketing time equations are also functions of the same set of predetermined variables. Price and selling time are co-determined, which implies that the error terms can be correlated across equations. This possible cross equation correlation calls for estimating the two separate equations as a seemingly unrelated system—the same method appropriate for estimating systems of consumer demand equations. This approach allows us to extend the basic hedonic price model by controlling for localized neighborhood market conditions, thereby eliminating the need to deal with the consequences of spatial correlation. In our models, the log of sales price is explained by the marketing time, house characteristics, subdivision name and location, and housing market conditions. TOM is also a function of the sales price, house characteristics, subdivision name and location, and housing market conditions.

As suggested above, these functions can be thought of as analogues to consumer demand functions for goods that are derived from neoclassical consumer theory.

$$\ln P = \sum_i \alpha_i x_i + \varepsilon_p$$

$$TOM = \sum_i \beta_i x_i + \varepsilon_\tau$$

Because the mathematical structure of this problem is parallel to the consumer's problem in demand theory that yields demand equations that are functions of the same predetermined variables, the price and selling time equations are also functions of the same set of predetermined variables for the seller search problem, summarized here as the vector **x**. Price and selling time are co-determined, which implies that the error terms can be correlated across equations. This possible cross equation correlation calls for estimating the two separate equations as a seemingly unrelated system—the same method appropriate for estimating systems of consumer demand equations.

3. Data and Variables

The selection of variables used in this study is based on previous research. For example, earlier studies specify the sale price of a dwelling to be a function of physical characteristics of the house, localized market conditions, location and time trend variables representing fixed effects for the exact geographic location, and year and season of sale, and set of variables of interest representing if a particular house is in a subdivision that uses words of interest to us in its name.

We use a sample comprising broker-assisted housing transactions completed between October, 1984 and April, 2005. The data are drawn from the Multiple Listing Service (MLS) sales reports for Baton Rouge, Louisiana, a medium size urban area that has been the subject for much academic housing market research. The sample period ends three months before Hurricane Katrina affected the area of study.

First, our analysis covers single family residential dwellings. In order to avoid outlier influence on our estimates, we exclude from the sample houses that take fewer than 14 or more than 400 days to sell; houses that sell for less than $40,000 or more than $900,000; houses with unusually small (less than 300 square feet) or large (greater than 5500 square feet) living area; and similarly for the area under roof net of living area (110 and 7000, respectively). We then restrict our attention to detached single family houses sold within a contiguous region within the urban area. The resultant data sets comprise 30,736 and 28,770 transactions.

The house characteristics include standard features such as number of bedrooms, bathrooms, fireplaces, age and its square, living area and its square, and net area and its square. Table 1 reports the means and standard deviations of the variables used in the empirical models. The sales price (*Price*), marketing time (*TOM*), number of bedrooms (*Bedrooms*), number of bathrooms (*Bathrooms*), number of fireplaces (*Fireplaces),* the age of the house (*Age*), and living area (*Living Area*) are drawn directly from the MLS report for each sale. The *Net Area* variable is calculated as the difference between the total square footage under roof less the square footage of living area, and it captures the size of utility rooms, garages, covered porches, carports, etc.

Location is indicated by a set of dummy variables that control for 265 census blocks, which are measured by the census value closest in time to the observed transaction. Fixed effects for year and season of sale are obtained using appropriately defined sets of dummy variables. In addition, neighborhood housing market conditions are measured in part by *Listing Density*, the number of competing houses that are for sale at the same time a house is on the market. Listing density measures the intensity of competition from other houses for sale per day on the market. A greater number of competing houses for sale surrounding a given house increases competition for buyers, but at the same time it can lead to shopping externality effects as the greater concentration of listings draws more potential buyers to the neighborhood. The signs of the coefficients on the listing density variables therefore reveal the relative strength of the spatial competition and shopping externality effects. The rationale for including neighborhood market conditions variables in the hedonic model is very simple. Intuitively, the number of houses for sale in a small neighborhood surrounding a particular house can have localized effects on the distribution of prospective buyers and sellers, the rationale typically used to justify spatial interdependencies in sales prices. A greater number of houses for sale increases the competition among sellers for buyers considering houses in the neighborhood—the localized competition effect. Similarly, a greater number of houses for sale may draw more prospective buyers to the neighborhood, potentially increasing the chance of matching a particular house with a buyer—the shopping externality effect.[6]

Equally as important in this application, this variable explicitly accounts for the type of neighborhood market conditions used to rationalize the need to correct for possible spatial correlation. We model the spatial competition effects directly and therefore obviate the usual rationale for applying spatial estimation methods. To further capture the neighborhood characteristics and atypicality effect, we also include the relative house size variables *Larger* and *Smaller*.[7] These variables measure the extent to which a given house is either larger or smaller than the average living area in the surrounding neighborhood.[8]

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[6] For detailed discussion on this part see Turnbull, G.K. and J. Dombrow, Spatial Competition and Shopping Externalities: Evidence from the Housing Market. Journal of Real Estate Finance and Economics, 2006, 32: 391-408.

[7] Haurin's model offers an explanation for why houses with unusual attributes sell for less and take longer to sell (Haurin 1988, Jud, Seaks and Winkler 1996). To capture the property atypicality effects we use an alternative to this model that is presented in Turnbull, Dombrow and Sirmans (2006).

[8] For more details on construction of these variables see Turnbull G.K., J. Dombrow and C.F. Sirmans, Big House, Little House: Relative Size and Value, Real Estate Economics, 2006, 34: 439--456

Thus, after controlling for the relative size effect, we argue that the subdivision name captures the pricing effect over and beyond the neighborhood characteristics.

It has been suggested that residential subdivision names provide information regarding the status and the environment of a particular house and a neighborhood to consumers. Because some aspects of the quality and benefits of a home or a residential property are not understood until it is owned for some time, consumers might rely on property names as a heuristic for quality when deciding which home to buy. Therefore, the image of a residential property conveyed through its name is expected to affect its selling price and marketing duration. Seeking to brand their products the way toothpaste makers and cola companies have for years, an increasing number of home builders are under pressure to differentiate their work from the dozens of other projects springing up nearby. However, as oak, bay, forest and other geographic or horticultural names become increasingly prosaic; more builders choose abstract names. In many cases, the name is designed to be attention-grabbing and evocative of a certain kind of lifestyle — real or imagined. Others believe that names are the best marketing tool when they convey realistic, evocative and place-sensitive information to buyers.

Using data from the Planning Commission of the City of Baton Rouge and Parish of East Baton Rouge, Louisiana we classified subdivision marketing names into themes. This method resulted in the analysis of over 1,720 subdivision names. Over 50 different names are associated with subdivisions for which we had no identifiable use while we matched about 143 to commercial use only. We eliminated another 30 names that are associated with mixed use developments with both residential and commercial property. Moreover, a subdivision's built environment, including the size, age, architectural style and the aesthetic quality, can create externality effects. In addition to the above described neighborhood characteristic controls, we used the subdivision vintage to control for the pricing effects of a subdivision's built environment. Thus, including subdivision vintage in our empirical models serves to capture the characteristics that subdivisions built during particular era have in common. However, this variable was unknown for 79 of subdivisions in our data set leaving us with over 1,400 distinct subdivisions. Once a name is established, its identity is projected via several social networks as well as through landscape features. Furthermore, subdivision names are also available in the real estate Multiple Listings Service, so that realtors and prospective buyers constantly evaluate a subdivision, in part, on its name. We have identified three themes; names projecting an environmental identity such as oaks, forest, and lake[9]; names projecting prestige such as manor, country club and estates; and names projecting physical location such as Jefferson, Airline and university[10]. Thus, the focus of our study is a set of dummy variables that indicate if the property is located in a subdivision with a name that includes our words of interest. Table 1 presents name categories and examples of subdivision names in each category. The totals represent the number of times each word appears in a different subdivision name in our data set. Our regression estimates include representative names from each theme group. Some of the names were used in earlier years but not in later developments. For example, *Manor* has been used in seven different subdivision names with the latest one being developed during early 1980s. On the other

[9] It appears that environmental names reflect a trend by builders to respond to preservationist concerns by giving an impression that developments are planned in harmony with the surrounding nature.
[10] Jefferson and Airline are major roads in Baton Rouge.

hand, in the early 1980s, the *Country Club of Louisiana (CCL)* was also in the early stages of development. More than two decades later, it has spawned dozens of other subdivisions off Highland and Perkins roads on the southeastern side of the city with the *Country Club Court* being developed during the early 2000s.

Table 2 summarizes the means and standard deviations of the variables included in the regression analysis. The dependent variable is house sale price with the mean of \$118,897 in our full sample and \$121,121 in a single family detached dwellings sample. Some of the variables that capture house attributes include the number of bedrooms (mean of 3.30), number of full bathrooms (2.05), living area in square feet (1967), and net area (710). The additional analysis of our data set reveals that the environmental theme names are used most often. For example, 12.4 percent of dwellings in our data set are in subdivisions with “oak” in the name and an additional 11.4 percent are in subdivisions with the word “forest” in the name. Just less than one percent of our sample is located in subdivisions with “manor” or “university” in the name.

4. Results

We estimate our model for the logarithm of selling price, ln(*Price*), and marketing duration, *TOM*. The set of right hand side variables comprise those defined earlier: *Bedrooms, Bathrooms, Fireplaces, Living area, Net area, Listing density, Vacant*, *Age*, relative house size variables *Larger* and *Smaller*, location controls for the census blocks, and year and seasonal fixed effects dummy variables. Thus, the basic model carefully controls for important pricing and selling time effects identified previously in the literature, including those associated with property atypicality. Following the basic model, we estimate an expanded model that introduces additional variables in order to capture all other neighborhood amenities that could influence selling price and marketing duration. For example, we include the distance to central business district, the distance to the nearest recreational area and the subdivision vintage.

We rationalize that homes in many subdivisions offer some subdivision specific amenities such as a clubhouse, walking trails, and the presence of community pools. While we cannot observe these characteristics directly in our data set, we create a new variable, *Distance_Park*, which measures the distance from the house *i* to the nearest recreational facility. Similarly, we create a measure to the central business district, *District_CBD.* In addition, to account for a subdivision's built environment we include a variable that captures the age of the subdivision, *SUB_age*. This variable is based on the date of first filing recorded by the Baton Rouge Department of Planning and Development. As a result, including subdivision vintage in our empirical models serves to capture the characteristics that subdivisions built during particular era have in common.

Furthermore, the single school district is coterminous with the unified city-parish government jurisdiction boundaries, a unique feature that minimizes spatial variation in local property tax rates, school spending, as well as other public services. Still, during part of the sample period students were randomly assigned to schools with parish-wide busing, thereby eliminating variation in expected school quality usually found across neighborhoods in other urban areas.

We estimate the price and marketing time equations as a joint system using seemingly unrelated regression (SUR). The SUR method accounts for expected cross-equation correlation induced by the fact that price and marketing time are simultaneously determined. The housing price and marketing duration equation parameter estimates for the house and neighborhood attributes are in line with previous literature. To keep the presentation concise, tables 3 and 4 only report the key parameter estimates pertaining to the subdivision name effects on price and marketing duration.[11]

The coefficients on the standard set of variables under the *House Characteristics* heading follow expectations. For example, the results suggest that number of bathrooms, fireplaces, living area, and net area have a positive effect on market value and are significant at the 1 percent level. In all models, living area is more valuable than net area and older houses sell for less.

The variables under the heading *Marketing Characteristics* capture real property marketing conditions. *Vacant* is a dummy variable indicating an unoccupied property. The coefficient on this variable indicates that vacant houses sell for a discount of about 6 percent and they require longer marketing time, an average of 10 additional days. In addition, the density of surrounding listings and unobserved house atypicality measured by *Larger* and *Smaller* variables are considered under marketing characteristic.

[11] Full model estimates for these tables are in an appendix available by request.

Intuitively, if both larger and smaller houses in a neighborhood are considered atypical by potential buyers, then it is harder to find buyers for such properties. Thus, these kinds of properties are expected to sell at a discount and require longer marketing time when compared with the same size houses in homogeneous neighborhoods. We find a negative coefficient on *Larger*, which indicates that larger houses in a neighborhood of smaller houses sell at a discount relative to large houses in large-house neighborhoods. At the same time, the positive coefficient on *Smaller* indicates that smaller houses in a neighborhood of larger houses sell at a premium relative to small houses in small-house neighborhoods. However, the coefficients on both variables in the TOM equation indicate longer marketing time.

When examining the subdivision names, our goal was to choose names representative of metropolitan Baton Rouge while controlling for characteristics such as location, age of the area, demographic and economic characteristics of the area. In essence, we identify subdivisions within census block groups with similar housing units and test if there are any pricing differentials that can be attributed to subdivision names. Figures 1 and 2 illustrate our data. We found words that suggest prestige, even seclusion and elitism, in use in Baton Rouge; our analysis includes words such as "country", "estate", and "manor" to represent this prestige category. These names vary greatly in popularity and frequency of use. For example, "estate" appears in 90 different subdivisions while "manor" appears in only seven. All three of the names appear statistically significant in the price equation. Houses located in subdivisions with words "country" and "manor" sell at 5 percent premiums. However, it appears that the rise in the popularity of "estates", reflected in the higher number of names with “estate” and the percentage of houses in subdivisions with “estate” in the name, affects housing values negatively. The coefficient on *Estates* in the price equation, although small in magnitude, is negative and statistically significant at the 10 percent level. At the same time, the prestige status communicated in the subdivision names has no statistically significant effect on marketing duration.

Names that highlight the location of the residential project are under the location theme and in our empirical analysis we focus on two: “University” and “Jefferson”. Subdivisions whose name contains the word “university” are mostly clustered around Louisiana State University while the word “Jefferson” reflects a geo-spatial relationship to Jefferson Rd., a major roadway that stretches from the edges of the city center to the southeast side of the parish boundary. Houses located in subdivisions with the word “University” in their names sell at over eight percent premiums. This is a significant premium equivalent to a $9,500 price increase for the average price house in our full sample. Neither of the two categories has a significant effect on marketing duration. The coefficient on “Jefferson” is also statistically positive but lower in magnitude. Yet, this coefficient is not robust to a model specification.

Overall, names projecting an environmental identity have increased in popularity over time. Natural features that are seen as distinctive selling features such as oaks, forest, lakes are increasingly symbolized in subdivision names. For example, “oak” appears in 99 different subdivision names, “lake” appears 63 times, and the “forest” appears 26 times. Even though a large number of subdivisions contain “oak” in their names, houses in these subdivisions sell at premiums of just over 4 percent but they require longer marketing time; TOM for these properties is longer by four days on an average.

The additional columns of table 3 present our model estimates when we introduce local area controls and when we re-estimate the model while bootstrapping standard errors. Our results remain robust except for the coefficient on *Jefferson,* which becomes statistically insignificant. It is worth noting that coefficients on distance variables show that the distance to the nearest park is not driving selling prices or marketing duration in the Baton Rouge housing market. In line with standard location theory, the coefficient on the distance to the central business district shows declining price gradients as we move away from the center. Interestingly, this model indicates that the vintage of the subdivision is an important determinant of house prices, but not marketing duration.

Next, we focus our attention on detached single family houses only. This subset of our full sample covers 28,770 observations sold over the same time period. Our results are shown in table 4. Again, we first estimate the model for the logarithm of selling price, ln(*Price*), and marketing duration, *TOM,* using the location controls for the census blocks. Then, following the basic model, we estimate an expanded model that introduces additional variables in order to capture all other neighborhood amenities that could influence selling price and marketing duration. And finally, we re-estimate this model with bootstrapped standard errors. The coefficients on our variable of interest that represent different themes in subdivision names are very similar to the full model estimates. The only notable difference is that the coefficient on *Manor* and *Forest* indicate that single family detached houses in subdivisions with names that include these words do not impact house prices or marketing duration.

5. Conclusion

We have proposed that an appropriate naming strategy can provide cues for consumers, which can expedite their purchase decision making process. Appropriately named subdivisions can promise an experience that a substantial number of consumers aspire to, creating demand and increasing the market prices of houses in the subdivision.

The findings of our study contain important implications for the industry professionals and researchers. Although, the name of a subdivision cannot embody all the characteristics of an ideal measure that a consumer may have in mind, our results suggest that a strategically named property can sell at higher prices. Market research of desirable property names can provide significant insight into the underlying factors that signal a price premium. However, sellers must be careful in their tradeoff as certain property names that can create a premium may have a longer than average marketing duration.

This article provides a framework for determining the extent to which property names can influence market prices of houses and whether these factors hold true under different market conditions. Further research should also be able to quantify the effect of the housing names on the long term changes in house values. The bottom line is that marketers of property, which holds value far beyond everyday consumer items, should employ the same rigorous, empirical study of naming effects on demand and price premiums as their counterparts selling soap and shoes.

Table 1: Subdivision Names Containing Selected Themes

Theme	***Total***	***Example***
Environmental		
Oak	**99**	**Hidden Oaks**
Forest	**26**	**Park Forest**
Lake	**63**	**Amber Lakes**
Prestige		
Country	**26**	**Country Club Colony**
Estates	**90**	**Blackwater Estates**
Manor	**7**	**Brightside Manor**
Location		
University	**14**	**University Acres**
Jefferson	**29**	**Jefferson Terrace**
Airline	**5**	**Airline Place**

Table 2: Description of Variables and Summary Statistics

Variable	*Description*	*Full Sample*		*Detached Single Family Sample*	
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Price	Selling Price	118897.5	74099.51	121121	75181.83
TOM	Time on market	87.59936	72.59785	87.31429	72.21799
Bedrooms	Number of bedrooms	3.298868	.6578875	3.354779	.6231028
Bathrooms	Number of bathrooms	2.049388	.5186306	2.057247	.5221206
Vacant	Vacant home dummy variable	.3035854	.4598132	.2956552	.4563447
Fireplaces	Number of fireplaces	.7056546	.5405339	.6991658	.5456428
Living Area	Square feet of living area	1966.885	666.0394	2000.005	667.1064
Age	Age of house	20.37018	15.91408	20.86594	16.14555
Net Area	Square feet of other	710.4483	340.5234	724.1387	343.9525
Age_sq	Age squared	668.1942	1118.2	696.057	1138.769
Living Area _sq	Living Area squared	4312230	3263865	4445034	3307978
Net Area _sq	Net Area squared	620689.2	809167.5	642676.1	829325.5
Smaller	Negative deviations from local mean living area	.0747277	.1110579	.0676414	.1032397
Larger	Positive deviations from local mean living area	.1159152	.2118468	.1203228	.2153652
DSF	Detached single family dummy variable	.9360359	.2446929		
TWN	Townhome dummy variable	.0441176	.2053598		
Listing Density	Competing listings weighted by days	2.497399	2.116366	2.50977	2.124408
Observations		***30736***		***28770***	

Table 3. SUR Parameter Estimates for Full Sample

	Base Model		***Expanded Model***		***Expanded Model (bootstrapped S.E)***	
Variables	Ln(Price)	TOM	Ln(Price)	TOM	Ln(Price)	TOM
House Characteristics						
Bedrooms	-0.0126***	-1.749*	-0.0216***	-0.199	-0.0216***	-0.199
	(0.0020)	(0.92)	(0.0020)	(0.95)	(0.00276)	(1.032)
Bathrooms	0.0150***	-0.329	0.0200***	-1.177	0.0200***	-1.177
	(0.0024)	(1.11)	(0.0024)	(1.12)	(0.00329)	(1.100)
Fireplaces	0.0176***	-3.272***	0.0206***	-3.796***	0.0206***	-3.796***
	(0.0020)	(0.94)	(0.0020)	(0.94)	(0.00245)	(0.960)
Age	-0.0129***	-0.234**	-0.0157***	-0.320	-0.0157***	-0.320
	(0.00021)	(0.097)	(0.00060)	(0.28)	(0.000813)	(0.298)
Age_sq	0.000132***	0.00309***	0.000138***	0.00271**	0.000138***	0.00271**
	(0.0000026)	(0.0012)	(0.0000026)	(0.0012)	(3.52e-06)	(0.00133)
Living Area	0.000795***	0.0216***	0.000769***	0.0260***	0.000769***	0.0260***
	(0.000011)	(0.0051)	(0.000011)	(0.0051)	(1.38e-05)	(0.00606)
Net Area	0.000169***	-0.00653**	0.000160***	-0.00506*	0.000160***	-0.00506
	(0.0000062)	(0.0029)	(0.0000062)	(0.0029)	(1.18e-05)	(0.00325)
Living Area_sq	-0.0000000531***	-0.000000882	-0.0000000504***	-0.00000136*	-5.04e-08***	-1.36e-06
	(1.69e-09)	(0.00000079)	(1.68e-09)	(0.00000079)	(2.18e-09)	(9.61e-07)
Net Area_sq	-0.0000000246***	0.00000128	-0.0000000224***	0.000000896	-2.24e-08***	8.96e-07
	(2.34e-09)	(0.0000011)	(2.32e-09)	(0.0000011)	(5.58e-09)	(1.25e-06)
Subdivision Name						
Country	**0.0497*** **	**4.338**	**0.0471*** **	**5.167**	**0.0471*** **	**5.167**
	(0.0081)	**(3.81)**	**(0.0081)**	**(3.83)**	**(0.00879)**	**(3.760)**
Estates	**-0.00650* **	**-0.922**	**-0.0112*** **	**-0.100**	**-0.0112*** **	**-0.100**
	(0.0037)	**(1.72)**	**(0.0036)**	**(1.72)**	**(0.00323)**	**(1.524)**
Manor	**0.0490*** **	**5.444**	**0.0313** **	**8.611**	**0.0313*** **	**8.611**
	(0.012)	**(5.78)**	**(0.012)**	**(5.79)**	**(0.0120)**	**(5.536)**
University	**0.0836*** **	**2.021**	**0.0844*** **	**1.932**	**0.0844*** **	**1.932**
	(0.013)	**(5.92)**	**(0.013)**	**(5.92)**	**(0.0215)**	**(5.265)**
Jefferson	**0.0151** **	**-3.607**	**0.00943**	**-2.546**	**0.00943**	**-2.546**

	(0.0071)	**(3.35)**	**(0.0071)**	**(3.35)**	**(0.00759)**	**(3.412)**
Oak	**0.0438*** **	**3.617***	**0.0426*** **	**3.860** **	**0.0426*** **	**3.860*** **
	(0.0040)	**(1.85)**	**(0.0039)**	**(1.85)**	**(0.00433)**	**(1.442)**
Forest	**-0.0116** **	**-1.458**	**-0.0151*** **	**-0.934**	**-0.0151*** **	**-0.934**
	(0.0058)	**(2.73)**	**(0.0058)**	**(2.73)**	**(0.00493)**	**(2.764)**
Marketing Characteristics						
Vacant	-0.0588***	9.936***	-0.0567***	9.546***	-0.0567***	9.546***
	(0.0019)	(0.89)	(0.0019)	(0.89)	(0.00192)	(0.910)
Smaller	0.203***	12.14*	0.203***	12.06	0.203***	12.06
	(0.016)	(7.36)	(0.016)	(7.36)	(0.0173)	(8.081)
Larger	-0.257***	11.34***	-0.233***	7.465*	-0.233***	7.465
	(0.0091)	(4.26)	(0.0091)	(4.28)	(0.0156)	(4.883)
Listing Density	0.000600	0.772***	0.000490	0.767***	0.000490	0.767***
	(0.00054)	(0.25)	(0.00053)	(0.25)	(0.000470)	(0.232)
DSF			0.0972***	-15.41***	0.0972***	-15.41***
			(0.0066)	(3.10)	(0.00841)	(3.655)
TWN			0.00723	0.811	0.00723	0.811
			(0.0078)	(3.70)	(0.0119)	(3.994)
Spring	0.00201	-3.518***	0.00155	-3.430***	0.00155	-3.430***
	(0.0025)	(1.16)	(0.0025)	(1.16)	(0.00239)	(1.198)
Summer	0.0131***	-8.734***	0.0128***	-8.778***	0.0128***	-8.778***
	(0.0025)	(1.16)	(0.0025)	(1.16)	(0.00225)	(1.159)
Fall	0.0177***	-8.205***	0.0169***	-8.150***	0.0169***	-8.150***
	(0.0026)	(1.22)	(0.0026)	(1.22)	(0.00240)	(1.190)
Local Area Controls						
Distance_Park			**0.00445**	**0.414**	**0.00445**	**0.414**
			(0.0042)	**(1.97)**	**(0.00592)**	**(2.202)**
Distance_CBD			**-0.0225*** **	**0.659**	**-0.0225*** **	**0.659**
			(0.0046)	**(2.15)**	**(0.00674)**	**(2.207)**
SUB_age			**0.00210*** **	**0.147**	**0.00210*** **	**0.147**
			(0.00050)	**(0.24)**	**(0.000701)**	**(0.235)**
Constant	10.83***	56.43***	10.95***	53.43***	10.95***	53.43***
	(0.020)	(9.28)	(0.033)	(15.7)	(0.0476)	(15.13)

Observations	30736	30736	30736	30736	30736	30736
R-squared	0.91	0.08	0.91	0.08	0.91	0.08

Standard error estimates in parenthesis.
Dummy variables for 265 census blocks and year sold are not reported in this table.
*indicates significance at the 10% level; **indicates significance at the 5% level; ***indicates significance at the 1% level.

Table 4. SUR Parameter Estimates for Detached Single Family Dwellings

	Base Model		***Expanded Model***		***Expanded Model (bootstrapped S.E)***	
Variables	Ln(Price)	TOM	Ln(Price)	TOM	Ln(Price)	TOM
House Characteristics						
Bedrooms	-0.0187***	-0.0381	-0.0189***	-0.0330	-0.0189***	-0.0330
	(0.0020)	(0.98)	(0.0020)	(0.98)	(0.00264)	(1.166)
Bathrooms	0.0241***	-0.938	0.0239***	-0.915	0.0239***	-0.915
	(0.0024)	(1.15)	(0.0024)	(1.15)	(0.00356)	(0.964)
Fireplaces	0.0226***	-3.677***	0.0228***	-3.693***	0.0228***	-3.693***
	(0.0020)	(0.97)	(0.0020)	(0.97)	(0.00230)	(1.022)
Age	-0.0130***	-0.0480	-0.0152***	-0.178	-0.0152***	-0.178
	(0.00021)	(0.10)	(0.00059)	(0.29)	(0.000795)	(0.322)
Age_sq	0.000131***	0.00135	0.000133***	0.00151	0.000133***	0.00151
	(0.0000025)	(0.0012)	(0.0000026)	(0.0013)	(3.68e-06)	(0.00136)
Living Area	0.000751***	0.0254***	0.000748***	0.0255***	0.000748***	0.0255***
	(0.000011)	(0.0053)	(0.000011)	(0.0053)	(1.67e-05)	(0.00610)
Net Area	0.000151***	-0.00542*	0.000151***	-0.00543*	0.000151***	-0.00543*
	(0.0000061)	(0.0029)	(0.0000061)	(0.0029)	(1.06e-05)	(0.00304)
Living Area_sq	-0.0000000467***	-0.00000131	-0.0000000464***	-0.00000132	-4.64e-08***	-1.32e-06
	(1.67e-09)	(0.00000081)	(1.67e-09)	(0.00000081)	(2.69e-09)	(9.92e-07)
Net Area_sq	-0.0000000195***	0.000000957	-0.0000000195***	0.000000950	-1.95e-08***	9.50e-07
	(2.28e-09)	(0.0000011)	(2.28e-09)	(0.0000011)	(5.04e-09)	(1.33e-06)
Subdivision Name						
Country	**0.0302*** **	**5.383**	**0.0330*** **	**5.179**	**0.0330*** **	**5.179**
	(0.0084)	**(4.04)**	**(0.0084)**	**(4.05)**	**(0.0116)**	**(4.288)**
Estates	**-0.0150*** **	**0.111**	**-0.0146*** **	**0.0629**	**-0.0146*** **	**0.0629**
	(0.0036)	**(1.75)**	**(0.0036)**	**(1.75)**	**(0.00375)**	**(1.630)**
Manor	**0.000803**	**6.692**	**0.00377**	**6.435**	**0.00377**	**6.435**
	(0.013)	**(6.04)**	**(0.013)**	**(6.05)**	**(0.0126)**	**(6.828)**
University	**0.0879*** **	**0.778**	**0.0873*** **	**0.866**	**0.0873*** **	**0.866**
	(0.012)	**(5.95)**	**(0.012)**	**(5.95)**	**(0.0230)**	**(5.563)**
Jefferson	**0.0184** **	**-3.083**	**0.0188** **	**-3.017**	**0.0188** **	**-3.017**
	(0.0074)	**(3.55)**	**(0.0073)**	**(3.55)**	**(0.00797)**	**(4.028)**

Oak	**0.0325*** **	**4.046** **	**0.0329*** **	**4.017** **	**0.0329*** **	**4.017** **
	(0.0039)	**(1.90)**	**(0.0039)**	**(1.90)**	**(0.00459)**	**(1.716)**
Forest	**-0.00505**	**-0.723**	**-0.00539**	**-0.756**	**-0.00539**	**-0.756**
	(0.0059)	**(2.85)**	**(0.0059)**	**(2.86)**	**(0.00474)**	**(2.819)**
Marketing Characteristics						
Vacant	-0.0589***	9.341***	-0.0589***	9.329***	-0.0589***	9.329***
	(0.0019)	(0.92)	(0.0019)	(0.92)	(0.00192)	(0.955)
Smaller	0.254***	9.699	0.249***	9.906	0.249***	9.906
	(0.016)	(7.90)	(0.016)	(7.91)	(0.0215)	(8.788)
Larger	-0.248***	7.115	-0.246***	7.023	-0.246***	7.023
	(0.0092)	(4.45)	(0.0092)	(4.45)	(0.0164)	(5.487)
Listing Density	0.000839	0.733***	0.000753	0.727***	0.000753*	0.727***
	(0.00055)	(0.26)	(0.00055)	(0.26)	(0.000438)	(0.226)
Spring	0.00182	-4.122***	0.00190	-4.126***	0.00190	-4.126***
	(0.0025)	(1.20)	(0.0025)	(1.20)	(0.00235)	(1.275)
Summer	0.0136***	-9.442***	0.0133***	-9.467***	0.0133***	-9.467***
	(0.0025)	(1.20)	(0.0025)	(1.20)	(0.00249)	(1.054)
Fall	0.0174***	-8.765***	0.0170***	-8.780***	0.0170***	-8.780***
	(0.0026)	(1.25)	(0.0026)	(1.25)	(0.00247)	(1.247)
Local Area Controls						
Distance_Park			**0.0165*** **	**-1.375**	**0.0165*** **	**-1.375**
			(0.0043)	**(2.08)**	**(0.00515)**	**(2.056)**
Distance_CBD			**-0.0371*** **	**2.199**	**-0.0371*** **	**2.199**
			(0.0047)	**(2.26)**	**(0.00595)**	**(2.108)**
SUB_age			**0.00194*** **	**0.114**	**0.00194*** **	**0.114**
			(0.00049)	**(0.24)**	**(0.000634)**	**(0.259)**
Constant	10.91***	42.95***	11.12***	30.96*	11.12***	30.96**
	(0.020)	(9.75)	(0.034)	(16.3)	(0.0460)	(15.56)
Observations	28770	28770	28770	28770	28,770	28,770
R-squared	0.91	0.08	0.91	0.08	0.91	0.08

Standard error estimates in parenthesis.
Dummy variables for 265 census blocks and year sold are not reported in this table.
*indicates significance at the 10% level; **indicates significance at the 5% level; ***indicates significance at the 1% level.

Figure 1: Location of the two residential subdivisions within the same census block.

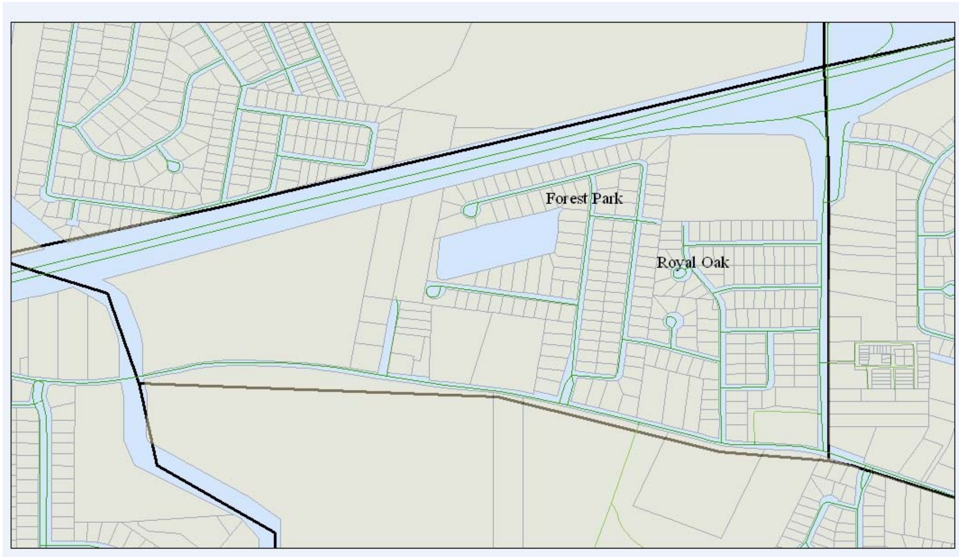

Figure 2: Location of the four residential subdivisions within the same census block.