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## Three essays on relative house size and house price

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# Three Essays on Relative House Size and House Price

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Dissertation submitted to the  
College of Business and Economics  
at West Virginia University in partial  
fulfillment of the requirements for the degree of

Doctor of Philosophy  
in  
Economics

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## Abstract

### ESSAYS ON RELATIVE HOUSE SIZE AND HOUSE PRICE

Susane J. Leguizamon

This dissertation is comprised of three essays in which I examine the influence that the size of the neighbors' houses have on predicted house price. I estimate the associated effect of a change in neighbor house size on predicted house price, how the effect changes when considering different reference groups, and how the effect changes when considering observations along the distribution. The analysis of results are framed within the context of behavioral explanations which are then compared to previous results regarding housing consumption behavior and status symbol consumption behavior. In Chapter 2 I estimate the change in predicted house price associated with an increase in the average size of the nearest neighbors' house size using a spatial autoregressive model. I find that individuals value an increase in absolute house size significantly more than they value a decrease in the size of the neighbors' house and yard. In Chapter 3 I use a spatial autoregressive hedonic model to examine change in predicted house price associated with a change in house size of four different reference groups: nearest neighbors, surrounding neighborhoods, the largest houses in the district and the smallest houses in the district. I find a positive associated effect of an increase in average house size of further neighbors and the smallest houses and a negative associated effect of an increase in the average house size of the nearest and largest houses. In Chapter 4 I use a spatial quantile model to estimate the associated effect for the 10<sup>th</sup>%, the 25<sup>th</sup>%, the 50<sup>th</sup>%, the 75<sup>th</sup>%, and the 90<sup>th</sup>%. I find consumers of the houses in the lower quantile of housing prices and the upper quantile of housing prices to exhibit an insignificant and small change in predicted house price associated with a change in the house size of the nearest neighbors. It is the consumers of houses in the middle and middle-upper housing price quantile which exhibit a significant and negative associated effect. These findings suggest that policies which redistribute may not be justified on the grounds of increased social welfare.

## Dedication

*I dedicate this dissertation to my wonderful family. To my grandmother, Donna, whose love and support I count as one of my most treasured possessions. To my mother and strongest ally, Sue, whom I am most indebted to for her guidance and friendship. Finally, I dedicate this to my father, Jerry, for his encouragement and support. It is his pessimism which I've inherited that has made my life to be one of constant pleasant surprises.*

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I would also like to thank my husband, Sebastian. Although I would have had a dissertation that was just as good and a graduate experience just as fulfilling, his presence made everything more fun. He, more than anyone else, is glad to see me finish and to finally stop talking about housing and relative status.

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# Chapter 1

## Purpose and Agenda

On March 12, 2008 the Senate Commerce Committees Subcommittee on Interstate Commerce, Trade and Tourism met to discuss whether the Gross Domestic Product is a valid proxy for the well being of the country. Among the many problems with using GDP, economist Robert Frank argued that a measure of relative income should be included because it was a better predictor of well being than absolute income (Frank, 2009). Dr. Frank's recommendation was formed on the basis of his extensive findings that, in general, individuals care more about their relative position in society than their absolute position (Frank, 1985).

The degree to which individuals value their relative standing in society is one that has important theoretical and policy applications. If relative consumption influences utility more heavily than absolute consumption, the utility function should be modified to reflect the reality. Similarly, if relative income is more valued than absolute income, government policies should account for that preference. Economists from Adam Smith to Karl Marx to have acknowledged that relative status/wealth matters, in some cases more than absolute status/wealth. Empirical evidence of this preference has emerged relatively recently that supports Dr. Frank's hypothesis that in large part, individuals value their relative income/status as much or more than their absolute income/status [(Luttmer, 2005), (Falk and Knell, 2004) (Ng and Wang, 1993) (Johansson-Stenman et al., 2002), (Solnick and

Hemenway, 1998), (Carlsson et al., 2007), (Carbonell, 2005), (Helliwell and Huang, 2005) and (Alpizar et al., 2005)]. However, these findings rely on stated preference survey data which have been shown to be biased by external factors and may not reveal true aggregate preferences accurately [(Varian, 2003), (Weaver and Swanson, 1974), (Perreault, 1975-1976), (Hubbard, 1942), (Farber, 1963), (Bertrand and Mullainathan, 2001), (Seymour Sudman and Schwarz, 1996), and (Tanur, 1992)].

My dissertation attempts to examine the extent to which individuals desire relative status by analyzing revealed, rather than stated, preferences. In particular, I compare the associated effect of a decrease in the size of the neighbors' house (where house size is a proxy for status) under various conditions. This approach avoids the shortfalls of using stated preference survey data and additionally, incorporates recent advancements in spatial methodology. In addition to the contribution to an old question, this dissertation reveals patterns in housing consumption previously unexplored.

In chapter 2 I employ a spatial hedonic model to isolate the willingness to pay for an increase in own house size and the willingness to pay for a decrease in the neighbors' house size. Following the hedonic theory first developed by Rosen (1974), a house is treated as a bundle of goods. With a large enough sample, it is possible to isolate the effect of a change in one of the housing variables, the number of bedrooms for example, on the housing price. This is thought to be the willingness to pay for that characteristic. However, the price of a home is also affected by the price of nearby homes. For instance, this implies that changing a housing characteristic that increases the price of your home will increase the price of your neighbor's house, which will further increase the price of your house. To control for this spatial dependence, we include a spatial component to our hedonic model, namely the spatial Durbin model.

I find that the effect of an increase in absolute house size is positive and significant, as expected. This gives evidence that individuals do value their absolute position in society and are willing to pay for it. Regarding a decrease in relative status (measured by an increase

in the size of the nearest neighbor's house), I find this effect to be negative and significant. This is consistent with the findings of the survey data literature; people value their relative position in society. However, in comparing the effect of the two issues, I find that individuals value an increase in their absolute house size *three times as much* as an increase in their relative house size. More specifically, individuals, on average, are willing to pay \$7,332 for an increase in absolute house size by 100 square feet from the mean, compared with \$2,257 for an equivalent increase in relative house size.

Chapter 3 incorporates the possibility of spatially dependent reference groups, with regards to relative status. It is likely that the effect of a change in neighbor house size on own house price of some groups are different than others. For instance, a decline in relative status of an individual to own family may affect utility differently than the decline in relative status of an individual to co-workers which may affect utility differently than the decline in relative status of an individual to others with similar educational backgrounds. The magnitude of the effect is dependent on the relationship of the individual to that reference group. In a similar way, it is reasonable to assume that the effect of a change in relative status would differ across space. The way in which relative status compared to your next door neighbor is important may be very different in the way that relative status compared to individuals in other states or countries is important.

To that I end, I determine how the effect on house price changes depending on the reference group. I categorize the neighbors into four reference groups including the nearest neighbors, further neighbors, rich neighbors (largest houses) and poor neighbors (smallest houses). I find that the relationship differs dramatically between groups and I draw on consumer behavior, marketing, sociology and economic literature to properly frame the results. In particular, a positive associated impact on house price of an increase in the size of the neighbors' house provides evidence of "reflected glory" consumption, while a negative associated impact provides evidence of envy.

Results suggest that the associated effect of an increase in the house size of further

neighbors and the poorest neighbors, is *positive* and significant (albeit small) on the house price. This suggests individuals are basking in the reflected glory of housing consumption of the rich and neighbors further away. The value of being in an area with larger houses appears to provide more value than the effect of the larger houses making own house seem relatively smaller. The associated effect of a decline in the house size of nearest neighbors and the poorest in the district is negative and significant. This suggests individuals are exhibiting envy towards housing consumption of the nearest neighbors and the poorest neighbors in the district. Intuitively, the relationship to the poorest neighbors may be such that the decline in perception of neighborhood quality, which may accompany a decrease in their house size, outweighs the benefit from having a relatively larger house.

In Chapter 4 I seek to uncover additional insight into a preference for relative house size. In particular, does relative house size behave as a normal good? If so, then we would expect the effect of an increase in relative size to be greater for higher price homes than lower priced homes. However, it could also be the case that it is the middle class who care most about "keeping up with the Joneses". The pursuit of relative status is often blamed for the poor savings rate and declining wealth of the lower and middle class, but does evidence of this behavior appear in the data?

Formally, this paper attempts to establish whether there exists any systematic patterns relating the housing price to a willingness to pay for an increase in relative house size. Employing spatial quantile regression analysis on housing price, housing characteristics and neighbor house price allows me to observe the effects around observations other than the mean. Quantile regressions are used to observe the effect of independent variables at different quantiles of the dependent variable. Housing, for instance, may be run on the 25%, 50% and 75% quantiles; the effect of the independent variables on the dependent variables around the bottom 25%, the 50% and the 75% of the housing prices are individually analyzed. If relative size behaves as a normal good we should expect the coefficient to increase in magnitude at the higher quantiles. Similarly, if the middle class or the lower class cares the most about

status, we would expect the coefficient to be largest in the middle quantiles or the lower quantiles, respectfully.

Findings suggest that it is the upper-middle class who care the most (in terms of willingness to pay) for an increase in relative size. The lower quantiles and the top quantile exhibit a much smaller effect that is statistically insignificant. A plausible explanation is that poorer individuals cannot "afford" to care as much about status while the wealthy have already achieved a high status (or, already have houses larger than the population in question). It is the individuals in between who can afford the pursuit of the Joneses and are willing to pay. This modified overall conclusion of the non-linear preference for relative house size highlights the usefulness of quantile regression analysis.

Additionally, the quantile regressions also picked up some interesting trends. Although relative house size exhibited the behavior detailed above, the effect of the neighbors' yard size is increasingly negative for higher quantiles. The more expensive the house, the larger negative effect an increase in the neighbor's yard size has. Similarly, the size of own yard has a larger (but positive) effect on house price along increasing quantiles while own house size has a decreasing effect.

I conclude this dissertation in Chapter 5 where I will summarize the results of the findings in the previous chapters and provide possible future extensions.

# Chapter 2

## Revealed Preference for Relative House Size

### 1 Introduction

Economists have acknowledged that individuals may be motivated in part by relative consumption, in addition to absolute consumption, at least as far back as John Stuart Mill (1806-1873).<sup>1</sup> In *The Theory of the Leisure Class*, Thorstein Veblen (1899) relied on relative status arguments to explain his theory of conspicuous consumption. Half a century later, Duesenberry (1949) further emphasized the effect of relative consumption on individual consumption decisions. For decades, mainstream economic models failed to account for this concern in the standard utility function, implicitly maintaining that individual utility is a function of absolute consumption only. Increased consumption leads to an increase in utility, regardless of the consumption levels of others. However, if relative consumption is important, it may not be the case that an increase in consumption yields an increase in utility. An individual's increase in consumption must be put in context of the level of consumption of his peers before deriving conclusions of changes in utility. Not until Easterlin (1974) did

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<sup>1</sup>This chapter is based on a collaborative essay with Justin Ross.

economists start to empirically examine the importance of relative status and possible policy implications. More recently Abel (1990) and Gali (1996) have contributed various models of interdependent utility functions.

Traditionally, the well-being of an individual is interpreted through their revealed preferences; the price of a good or service reflects at least the amount of utility it generates for the consumer. Thus, prices provide some indicator of individual utility from consumption. However, some behavioral economists argue individuals often depart from the bounds of the rational economic agent, causing prices to reflect inaccurate measures of generated utility. Frank (1985) describes two significant drawbacks to the standard economic agent model. The first is that individuals can make systematic errors in judgement. They act in ways that they later regret once they realize the consequences of their decision. The second drawback is the implicit assumption that individuals can efficiently process information. The rational agent model assumes information is processed instantaneously and correctly, but in reality it may be the case that individuals arrive at conclusions that are not in their best interest. This is caused by an inability to transform information into a decision that maximizes their well-being. In both cases, the regret felt implies that individuals value the good less than the purchase price. For these cases, price can no longer be used as a proxy for a minimum utility generated by consumption.

This argument has motivated the use of subjective utility measures to derive conclusions about individual happiness. Stated preference methods, survey data in particular, have been exclusively used to determine true preferences and make inferences regarding the demand for positional goods in terms of relative status. The use of stated preference methods for empirical analysis is justified on the grounds that it allows economists to ask interesting questions about non-market goods. However, the validity of survey data has been questioned extensively in the literature.

In particular, survey data results have been shown to be influenced by factors not related to the issue being studied. Weaver and Swanson (1974) found significant evidence of bias due



to respondent characteristics. Using verifiable employment data, they found that 84 percent of respondents overstated their salaries, only 65 percent reported their true seniority and 10 percent of individuals surveyed inaccurately reported their own birthdate. Jenkins (1941) discussed a source of bias resulting from ordering of questions, “leading questions,” and use of vague terms. Additionally, the age and gender of the interviewer (Benney et al., 1956), ethnic, social class and racial variation between the interviewer and interviewee (Hyman et al., 1954), the context of the interview (Jaeger and Pennock, 1961) and whether some responses are thought to be “socially desirable” (Edwards, 1957) are all noted to affect the outcomes of survey data (Farber, 1963). More recently, Bertrand and Mullainathan (2001), Seymour Sudman and Schwarz (1996), and Tanur (1992) have provided further evidence that the order of possible answers given and a respondents desire to impress the surveyor, either with on-the-spot formulated opinions or true opinions altered out of fear of having a “wrong” opinion, also influence the outcomes of survey data. These limitations of survey data suggest that alternative approaches are beneficial to determine the robustness of conclusions drawn from that literature.

In this chapter I test the demand for absolute and relative status with a revealed preference approach. Using a hedonic price spatial model, I examine whether individuals are willing to pay for larger houses relative to their neighbors’ after controlling for the effect of neighbors’ housing characteristics and price on own house price. This analysis contributes to the literature in the following three ways. First, this paper derives a measurable magnitude of the importance of relative status. An exact willingness to pay for an increase in relative status is elicited based on observed consumer behavior in the housing sector.

Second, I consider the effect of relative status compared to the effect of absolute status. Even if individuals place a premium on relative status, does this effect trump the effect of absolute status? Current happiness literature suggest that individuals are willing to forgo an increase in absolute status to experience an increase in relative status. If this is true, this implies individuals would pay more for a house in a neighborhood in which the neighbors’

houses are relatively smaller than for the same house in a neighborhood where the neighbors' houses are relatively larger. In deriving and comparing the willingness to pay for absolute and relative increases, this paper is the first to empirically answer this question.

Third, this chapter provides a new approach to test the validity of stated preferences in the market. The likelihood of individuals to behave in ways consistent with declarations has an important impact on the growing happiness literature and the use of survey data in general. While not attempting to credit or discredit the method, these results highlight the need for overlapping analysis. This paper is organized into four remaining sections. Section 2 reviews the literature, section 3 describes the methodology and data employed, section 4 presents the results and discussion and section 5 concludes.

## **2 Literature Review**

### **2.1 Relative Status**

Relative wealth and status have always been acknowledged as playing a role in consumption decisions. Utility derived from consumption should be put in the context of the level of consumption of others. Individuals are affected by their relative place in society; having a higher place increases utility, *ceteris paribus*. Similarly, individuals experience a decrease in utility when they occupy a lower position in society. Often, the desire for status translates to a desire for perceived status and individuals value appearing to occupy a high position in society. Historically, there was an advantage to appear the most fit, most beautiful, and/or most intelligent. The perception resulted in a higher share of scarce resources because others deferred to those of a higher status. Even today, more beautiful people experience higher wages and less beautiful people are penalized through lower wages (Hamermesh and Biddle, 1994). Clearly, there is a reward for status.

Frank (1985) describes the desire for relative status in part as a desire for “positional goods.” These are scarce goods, characterized by a position within the context of society.

The largest house, biggest car, best looking are all goods for which there exists only one by definition. Even if every individual got a raise, only one individual is the highest paid. The scarcity of positional goods coupled with rising wages, has caused the emphasis on relative status to grow in recent decades. Frank depicts a “positional treadmill” in which all members of society are working more to increase their wealth to gain status. Since everyone is doing it, the relative position of individuals in the society has not changed and everyone is worse off (from working more hours). This desire for position in society may stem from jealousy, envy or are remnants of earlier societies who distributed goods based on relative position. In a recent op-ed in the *The New York Times*, Frank made this point specifically with respect to housing size:

But beyond a certain point, when everyone builds bigger, the primary effect is merely to raise the bar that defines the size of home that people feel they need.

(BU5, March 22, 2009)

The desire for position in society creates a market for status symbol goods. In large societies where it is difficult to rank individuals, status symbols appear to act as a proxy for relative standing. Housing in particular can be considered a status symbol due to the nature of homeowners. Shelter in general may be considered a necessity, and consequently consumption may reflect a need for space rather than a desire for status, however, these low levels of housing consumption occur in the rental market rather than the buying market. It is assumed that individuals purchasing a house, or increasing the size of a house they own, are purchasing a status symbol because basic shelter can be obtained at a much lower cost than the price of a house.<sup>2</sup> As such, housing provides an excellent tool to study the nature of status symbols, relative status in particular.

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<sup>2</sup>It may still be argued that an increase in house size is for consumption use rather than status. However, if the number of rooms in the house are explicitly controlled for, any increase in size is not adding more rooms, only increasing the current ones in size. Doing so yields consistent results. Furthermore, when the sample was limited to houses over 3,000 square feet, for which an increase in house size is unlikely desired for consumption use, the results are robust.

## 2.2 Economics of Happiness

With regards to relative status and happiness, survey data analysis has consistently yielded the conclusion that individuals value relative status or position to such an extent that it may be greater than the value of absolute status or position. Using this type of data Solnick and Hemenway (1998), Johansson-Stenman et al. (2002), Carlsson et al. (2007) and Alpizar et al. (2005) found individuals prefer to have a higher consumption level relative to their peers and have a lower absolute level of consumption rather than have a higher absolute consumption level but a lower level relative to their peers. The survey typically consists of questions such as, “On a scale of 1-7, how happy are you in general?” followed by a question similar to “If your neighbors income were to rise by ‘X’ percentage, how happy would you be?” The researcher isolates the effect of a change in relative status by controlling for other variables including income, religion, location, education, age and family characteristics. Most recently, Luttmer (2005) matches various indicators of well-being with self reported levels of happiness and finds suggestive evidence that there exists a negative effect of neighbors’ earnings on own well-being. Falk and Knell (2004) and Ng and Wang (1993) find that relative income is at least as important of absolute income. On the job, Clark and Oswald (1996) find that relative wage rates are inversely related to reported satisfaction. Internationally, Carbonell (2005) and Helliwell and Huang (2005) have found similar results using German and Canadian data, respectively.

While revealed preference methods of utility analysis are criticized for their assumption of consistent consumer rationality, stated preference methods face limitations as well. In addition to previously discussed limitations regarding question bias, it is also feasible that inaccurate or untruthful (whether intended or a result of self-ignorance) self assessments can occur. The market requires a cost in the form of price to obtain truthful preferences whereas answering survey questions does not. Additionally, gauging feelings or levels of satisfaction is hard to accurately obtain and compare between individuals. Even if individuals can identify their levels of happiness and choose to tell the surveyor, it does not hold that the responses

mean the same thing between individuals (Varian, 2003). Two equally happy people may interpret the scale of responses differently and provide differing answers.

Practitioners acknowledge these drawbacks but often point to the fact that (1) psychologists have used them consistently in research and find the method to be sound (2) responses are correlated with predicted physical reactions (3) suicide rates are negatively correlated with happiness (Alesina et al., 2003) (4) there are often strong theoretical microfoundations to the models tested and (5) there are consistent results of survey data between and within countries as evidence of accuracy (Luttmer, 2005). Survey data results are accepted on the grounds that the variables tested are not readily observable in the market and thus hard to extract using traditional economic data. However, it is expected that if individuals do value relative status, they would be willing to pay for an increase if given a market.

A notable exception to the use of survey data is the finding that the number of suicides, controlling for own income, increases when the income of the reference group increase (Daly and Wilson, 2006). Although the comparison of absolute and relative income is not highlighted, the authors found that the effect of the reference group income is greater than the effect of own income. However, when income is treated as exogenous, the effect of own income becomes greater than the effect of reference group income. The authors concede that income is likely to be an endogenous trait of individuals who successfully commit suicide, but this analysis is relegated to a robustness check.

## **2.3 Hedonic Price Models**

Empirical researchers have increasingly used the hedonic price method to derive an implicit price for a good in some types of non-observable markets, although never before to answer questions about relative versus absolute status. Rosen (1974) is considered to have first developed the formal theory of hedonic markets. The theory stipulates that the price of any given house represents the price for a bundle of goods, both observable goods and unobservable goods. Observable goods include house amenities such as bedrooms, bathrooms, yard

size and architecture, while unobservable goods include non-physical housing attributes such as school quality, air quality and neighborhood characteristics. Given the choice of many different houses, a consumer can choose the combination of goods that maximize their utility within a given budget. With a large enough sample size it is possible to hold all but one of the housing goods constant and observe the change in housing price from changing the single good. The change in housing price can be interpreted as the willingness to pay for that good. This can be done for all goods, the sum of which is the total price of the house in equilibrium.

In practice, the willingness to pay is derived by holding housing price as the dependent variable and the different housing goods as the independent variables. The coefficients of the independent variables provide us with the effect of that variable on housing price. Hedonic models have been used to estimate the relationship between house price and hazardous waste sites (Kohlhase, 1991), (Nelson et al., 1992), (Hite et al., 2001), environmental quality (Brasington and Hite, 2003), air pollution (Smith and Deyak, 1975), (Kiel and McClain, 1995), (Chattopadhyay, 1999), (Beron and J. Murdoch, 2001), (Kim et al., 2003b) and water pollution (Hoehn et al., 1987). By isolating the effect of a change in a particular characteristic on housing price, the willingness to pay can be used as a proxy for utility generated from consumption.

This paper most closely follows that of Brasington and Hite (2003). They used a hedonic spatial model to estimate the relationship between housing price and environmental quality and derived a demand curve for environmental goods. Using the spatial Durbin model specifications, they established a negative relationship between distance to environmental hazard and housing price while uncovering significant evidence of spatial effects. They then derived the implicit price using 2SLS with proxies for endogenous variables and found the price elasticity of demand for environmental quality to be -0.12. This follows other literature where Beron and J. Murdoch (2001) found a price elasticity of visibility to be -0.0024, Bender et al. (1980) found the price elasticity of air quality to be between -0.503 to -0.262 and Zabel

and Kiel (2000) found the price elasticity of demand to be -0.479 for ozone. However, hedonic models prior to Brasington and Hite (2003) did not incorporate spatial dependence which has been shown to be statistically significant. I use the spatial hedonic model specified by Brasington and Hite (2003) but will incorporate the effect of relative status on housing price.

## 3 Methodology and Data

### 3.1 Data

I test the model using Brasington's housing data set (Brasington, 2001). The data includes over 40,000 observations of year 2000 fair market arms' length real estate transactions for owner-occupied housing in three metropolitan areas of Ohio. Ultimately I estimate our econometric model separately by MSA classification and report the results from the each of the three: Cleveland ( $n = 11,871$ ), Cincinnati ( $n = 13,115$ ), and Columbus ( $n = 16,020$ ).

The data set provides detailed information of housing features as well as characteristics of their census block groups for each of the observations. All variables are listed and described in Table 2.1. Housing specific data was used whenever possible with some variables representing the average within a census block group. Consequently, model conclusions are based on aggregated data at the housing level but some variables are described as averages of their respective census block group. The means and standard deviations for each of the variables can be found in Table 2.2.

### 3.2 Spatial Hedonic Price Model

The standard hedonic model follows the vector form econometric model:

$$\nu = X\beta + \varepsilon, \tag{2.1}$$

Table 2.1: Variable Definition and Source

Variable Name	Definition
House Price <sup>1</sup>	Sale price of house in 2000 dollars
House Size <sup>1</sup>	Size of house in thousands of square feet
Yard Size <sup>1</sup>	Size of yards in acres
Maximum House <sup>3</sup>	Equals 1 if the house is the largest house of nearest neighbors, otherwise 0
Onestory <sup>1</sup>	Equals 1 if the house is one story, otherwise 0
Air Conditioning <sup>1</sup>	Equals 1 if the house has air conditioning, otherwise 0
Fireplace <sup>1</sup>	Equals 1 if house has fireplace, otherwise 0
Full Baths <sup>1</sup>	Number of full baths in house
Part Baths <sup>1</sup>	Number of partial baths in the house
Age <sup>1</sup>	Age of house in hundreds of years
Deck <sup>1</sup>	Equals 1 if house has a deck, otherwise 0
Proficiency <sup>2</sup>	Difference between percentage of district students passing the 2000-2001 9th grade proficiency test and the average pass rate in the MSA
Expenditure Per Pupil <sup>1</sup>	Average amount spent per student by school district in thousands of dollars 2000-2001
Mill Rate <sup>1</sup>	Effective mill rate for 2000 Class 1 property (agricultural and residential) in the school district
Pollution <sup>1</sup>	Tens of thousands of pounds of total fugitive emissions (leaks, spills, etc) and confined air stream releases in the census block year 2000
Racial Fract. <sup>1</sup>	Leik (1966) index of census block racial heterogeneity with 0 being homogenous and 1 being completely heterogenous
Income <sup>1</sup>	Median income of census block in 2000, in thousands of dollars
Crime <sup>1</sup>	Total offenses in the police district, per hundred people, year 2000

Sources: (1). Obtained from Brasington and Haurin (2006) (2). Obtained from Hall and Ross (2008)



Table 2.2: Summary Statistics

<b>Summary Statistics: Mean Values</b>	
<b>Variable</b>	<b>Columbus</b>
House Price	145696.00
House Size	1650.79
Proficiency	48.31
Expenditure/Pupil	8281.49
Onestory	0.38
Bathrooms	2.12
Rooms	6.30
Age	33.17
Tax Rate	34.47
Pollution	1968.56
Racial Fract	0.13
Income	54677.31
Crime	97.67

where  $\nu$  is an  $n \times 1$  vector representing the natural log of housing prices,  $X$  is the  $n \times m$  vector of  $m$  explanatory characteristics of the observation and  $\varepsilon$  is normally distributed with constant variance and zero mean.<sup>3</sup> The individual observations consist of a individual house, and the included explanatory variables consist of owner, structural, location, and neighborhood characteristics. The latter two characteristics often motivate the use of incorporating methods to control for spatial spillovers effects<sup>4</sup>.

Typically, there are two models used to account for this type of spatial dependence, the spatial autoregressive (SAR) and the spatial error model (SEM). The SAR consists of a spatial lag of the dependent variable, whereas the SEM specification corrects for spatial correlation in the disturbance term. All the previous research conducted using the Brasington

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<sup>3</sup>See Green and Malpezzi (2003) for more details on the history and advantages of the semi-log functional form in hedonic regressions.

<sup>4</sup>It has been noted that a selection bias of consumers who end up purchasing the house may exist. In theory a two-stage Heckman model can account for the missing observations of houses and individuals who were not a part of any transaction. In practice, the data set is comprised of actual transactions, not assessed values. Any effort to conduct a probit model would be redundant, as the probability of individuals in our data set purchasing the house is one. In any case, the selection of houses sold in a given year can be assumed to be a random sample of the general population of houses and consumers.

Table 2.3: Bayesian Model Selection Probabilities for Columbus Sample

NN	prior r-value									
	30	10	9	8	7	6	5	4	3	2
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
6	0.078	0.080	0.075	0.086	0.076	0.081	0.084	0.075	0.086	0.086
7	0.019	0.019	0.018	0.019	0.020	0.019	0.018	0.020	0.020	0.021
8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Ohio housing dataset I have found has tested and concluded that the SAR specification is the most appropriate model. I present model selection statistics later in this paper, but the tests were supportive of the previous literature, and as such I limit the discussion to the SAR model. In vector form, the SAR model is specified as

$$\nu = \rho W\nu + X\beta + \varepsilon. \tag{2.2}$$

Equation (4.2) includes the dependent variable on the right-hand side of the equation, lagged by the  $n \times n$  spatial weight matrix  $W$ . Since the Brasington dataset includes the latitude-longitudinal coordinates of the individual houses, the weight matrix is based on the  $N$  “nearest neighbors,” where  $N$  is the chosen by the researcher and supported with model selection tests and results are shown in Table 2.3.<sup>5</sup> The matrix  $W$  then identifies which observations are to be considered spatially interdependent by assigning a weight of  $1/N$ , and listing zeroes the remaining elements as well as on the diagonal. The calculation of  $W \times \nu$  results in  $W\nu$  representing the average sale price of a observation’s neighbors.

While OLS is be biased and inconsistent with the inclusion of  $W\nu$  in Equation (4.2),

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<sup>5</sup>See LeSage and Pace (2009b, p.169-173) for details on Bayesian model selection method for alternative weight matrices, which was employed in this paper.

spatial dependence can be incorporated in the same manner among the independent variables  $X$  without controversy. In order to test the relative status effects, much of this paper will focus on comparing behavioral responses to changes in variable  $X_j$  against changes in  $W \times X_j$ . If all non-intercept variables in  $X$  have their spatial lag incorporated, then this model is commonly referred to as the spatial Durbin model, but in practice multicollinearity often undermine the implementation of a spatial lag on every independent variable.

Our first model will estimate the behavioral response to changes in the size of the property (*ysize*) and the structure (*hsize*) against the nearest neighbor spatial lag of these variables (*Whsize* and *Wysize*). Additionally, in following the real estate adage “never buy the largest house on the block,” I include an indicator for observations that are the largest of their nearest neighbors (*maxsize*):

$$\nu = \rho W\nu + \beta_0 + \beta_1 hsize + \beta_2 ysize + \beta_3 Whsize + \beta_4 Wysize + \beta_5 Maxsize + X\beta_6 + \varepsilon. \quad (2.3)$$

The equation specified in (2.3) will be referred to as Model I. As a robustness check, a Model II will be specified to include the spatial lag of the other independent variables in  $X$  that are specific to the housing unit itself. Spatial lags of neighborhood characteristics tied to each observation tended to be very collinear and were therefore excluded.

Standard economic utility theory predicts that individual utility increases with consumption, which would be reflected in  $\beta_1$  and  $\beta_2$  taking positive values to reflect a greater willingness to pay for larger properties and units. To the extent that these individuals desire a greater relative status,  $\beta_3$  and  $\beta_4$  would be negative and  $\beta_5$  positive. In other words, if relative status is important to homeowners, the larger a neighboring house is the lower utility becomes for their own house becomes, and a lower willingness to pay should be reflected in  $\nu$ . Furthermore, those who value relative status might be willing to pay a premium to be the largest among the neighbors, so  $\beta_5$  should be at least non-negative. These expectations

Table 2.4: Expectations of Signs in Equation (2.3) for Relative and Absolute Status Hypotheses.

Theory	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$	$\beta_5$
Relative	+/0	-	+/0	-	+
Absolute	+	0	+	0	0

are summarized in Table 2.4.

Comparing  $\beta_1$  to  $\beta_3$  and  $\beta_2$  against  $\beta_4$  will give us estimates of the marginal willingness-to-pay for absolute versus relative changes in status. For instance, if every person in the neighborhood were to build a 100 foot addition on their structure and their preferences matched the expectations summarized in Table 2.4, then the the sign on the net effect of  $\beta_1 + \beta_3$  would reveal whether the absolute effect dominates the relative effect, or vice versa.

If  $\beta_1 + \beta_3$  is negative, it would indicate that individuals value relative status more than absolute status, and suggests that an individual would be willing to pay more for a small house in which his neighbors have even smaller houses. Equivalently, he would pay less for a large home in which his neighbors have larger homes than him. In surveys, this comparison is analogous to the question, “Would you rather make \$50,000 a year if those around you only made \$30,000 than make \$100,000 if those around you made \$140,000?”. However, if  $\beta_1$  is found to be larger than  $\beta_3$  in absolute value, individuals are revealing a stronger preference for absolute status. The same analysis applies to yard size with  $\beta_2 + \beta_4$ . Note that while we can draw the qualitative intuition of the relative effects from these coefficients, to quantitatively interpret their full marginal impact the spatial multiplier effect of the lagged dependent variable must be considered.

For robustness, I extend the model in Equation (2.3) to include the spatial lag of other house-structure specific variables, such as an indicator for having more than one levels, central air, a fireplace, and deck, as well as the number of full baths and age of the structure. I refer to this extension of Equation (2.3) as Model II.

I employ the Bayesian robust heteroskedastic estimation procedure defined in LeSage and Pace (2009b, p.146-149). Letting  $Z$  be the control variables specified in Equation (2.3), the Bayesian spatial heteroskedastic model is specified as:

$$\begin{aligned}
\nu &= \rho W \nu + Z \beta + \varepsilon \\
\varepsilon &\sim N(0, \sigma^2 V) \\
V_{ii} &= v_i, \quad i = 1, \dots, n, \quad V_{ij} = 0, \quad i \neq j \\
\pi(\beta) &\sim N(c, T) \\
\pi(r/v_i) &\sim iid \chi^2(r), \quad i = 1, \dots, n \\
\pi(\sigma^2) &\sim IG(a, b) \\
\pi(\rho) &\sim U(0, 1)
\end{aligned} \tag{2.4}$$

The prior distributions are indicated using  $\pi()$ .<sup>6</sup> The variance scalars  $v$  allow for the direct estimation of the variance among the observations, rather than imposing the assumption that the variance is constant. Large estimates of  $v_i$  indicate the presence of heteroskedasticity or outliers, and down weight their influence within the data set. Hyperparameter  $r$  indicates the degrees of freedom in the  $\chi$  distribution and is chosen by the researcher. A low value, like four, is used to indicate a belief in heteroskedasticity or outliers, while a larger value can indicate a belief in homoskedasticity. The prior distributions on  $\sigma^2$ ,  $\beta$ , and  $\rho$  follow an inverse gamma, normal, and uniform distribution.

Since defining the number of nearest neighbors in the spatial weight matrix is more of an empirical question than one with theoretical support, the Bayesian model comparison method described in LeSage and Pace (2009b, p.169-173) is employed to determine which definition would be most likely to generate the data. The results in Table 2.3 demonstrate the results of this estimation for each MSA. Table 2.3 indicates that the data in Cleveland and Cincinnati are most likely generated in models that use a weight matrix that includes

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<sup>6</sup>The prior values assigned to the distributions in Equation (2.4) were  $c = a = b = 0$ ,  $r = 4$ , and  $T = 10,000$ .

the six nearest neighbors, whereas Columbus requires seven.

Our suspicion is that the Columbus MSA will yield results that are most reflective of the actual behavioral effects. Cincinnati is on the edge of the state border, and our data only contains housing sales that took place in Ohio. As such there are probably cross-state confounding factors in Cincinnati. For Cleveland, the MSA definition may be a bit restrictive in representing the space over which people choose to live in, as the Akron and Youngstown MSAs match closely. In fact, these three MSAs are often referred to as the Greater Cleveland Metropolitan Area. Since counties must belong to only a single MSA, even though a significant portion of the population may commute from Youngstown or Akron to Cleveland, those counties will still not get counted in the Cleveland MSA definition if they do not reach the benchmark chosen by the MSA. By comparison, Columbus is in the center of the state and is not nearly as integrated with other nearby MSAs. With this in mind, all three MSA data sets are estimated and have their results presented.

### **3.3 Variable Selection**

The price of a house is influenced by the quality of the house and the quality of the neighborhood. I assume that the quality of a house is measured by the size, number of rooms, presence of a deck or pool, air conditioning, fireplace, yard size and age of the house. An increase in amenities should yield a higher price while the age of the house may have a positive impact (if it has historical appeal) or negative (if it will require expensive upkeep). Additionally, literature suggests that the quality of the school district, the tax rate, the degree of racial fractionalization, the crime rate and the level of pollution are influential variables on neighborhood quality (Brasington and Hite, 2003). School quality has been shown to be a function of test scores and expenditure per pupil (Brasington, 1999) so is measured therefore by both the difference between the percentage of students passing the 9th grade proficiency exam and the average pass rate in the MSA and the expenditure per pupil by district. The houses located in areas with better schools will command a higher price.

The crime rate, degree of racial fractionalization and the level of pollution, should reduce the value of the house, and consequently, have a negative effect. Pollution in this case is measured as the tens of thousands of pounds of fugitive emissions and air stream releases in the census block. The tax rate effect could be positive or negative; tax rates can be a burden on citizens and/or act as a proxy for public good provision. The neighborhood quality measures are taken from averages of smaller census block groups and the values act as representative for houses within that group while the housing quality measures are taken from each house specifically.

## 4 Results

The spatial Bayesian heteroskedastic results for Models I and II estimated for each city are presented in Tables 2.5 through 2.10. Bayesian regressions estimate a distribution rather than a point, and as a series of descriptive statistics are used to describe those distributions: Mean ( $\mu$ ), standard deviation ( $\sigma$ ), Bayesian p-value, and the 2.5<sup>th</sup>, 5<sup>th</sup>, median, 95<sup>th</sup>, and 97.5<sup>th</sup> percentiles. While statistical significance has no meaning in Bayesian statistics, it is common to examine analogous statistics such as the 95% credibility interval, which is the area between the 2.5<sup>th</sup> and 97.5<sup>th</sup> percentiles. For instance, 95% of the coefficient distribution for yard size on Table 2.5 lies between 0.075 and 0.091. Similarly, a Bayesian p-value reports the area of the distribution on the opposing side of the mean. On Table 2.5, having a house larger than any others in the nearest neighbor weight matrix (Maximum House) has an expected value of -0.034 and a Bayesian p-value of 0.007. The Bayesian p-value indicates that  $(1 - 0.007) = .993$  is the area of the distribution that is also positive.

Columbus estimates for Models I and II are presented in Table 2.5 and 2.6, respectively. For the Model I estimates in Table 2.5, the size of a house has a clear positive, but negative quadratic effect on the natural log of its price. Before taking into account the spatial multiplier effect, the 95% credibility interval lies between 0.252 and 0.315, with an expected value

Table 2.5: Columbus Bayesian Spatial AR Linear Regression Posterior Estimates of Model I

<b>Dep: ln(hprice)</b>	$\mu$	$\sigma$	p-value	$\beta^{.025}$	$\beta^{.05}$	$\beta^{.5}$	$\beta^{.95}$	$\beta^{.975}$
Intercept	4.610	0.082	0.000	4.453	4.480	4.609	4.745	4.771
House Size	0.309	0.010	0.000	0.289	0.292	0.309	0.326	0.329
House Size <sup>2</sup>	-0.011	0.002	0.000	-0.015	-0.015	-0.011	-0.008	-0.007
ln(Yard Size)	0.083	0.004	0.000	0.075	0.077	0.083	0.090	0.091
W-House Size	-0.105	0.006	0.000	-0.117	-0.115	-0.105	-0.094	-0.092
W-ln(Yard Size)	-0.094	0.006	0.000	-0.107	-0.105	-0.095	-0.084	-0.082
Maximum House	-0.034	0.014	0.007	-0.060	-0.056	-0.034	-0.011	-0.007
One Story	0.001	0.000	0.000	0.001	0.001	0.001	0.002	0.002
Air	0.026	0.002	0.000	0.022	0.022	0.026	0.029	0.029
Fire	0.024	0.004	0.000	0.017	0.018	0.024	0.030	0.032
Full Baths	0.059	0.004	0.000	0.052	0.053	0.059	0.065	0.066
Part Baths	0.036	0.003	0.000	0.031	0.032	0.036	0.041	0.042
Age	0.067	0.004	0.000	0.059	0.061	0.067	0.073	0.074
Age <sup>2</sup>	0.032	0.004	0.000	0.024	0.026	0.032	0.038	0.039
Deck	-0.287	0.018	0.000	-0.322	-0.316	-0.287	-0.259	-0.253
Proficiency	0.204	0.015	0.000	0.175	0.180	0.204	0.229	0.233
Per Pupil Sending	0.054	0.013	0.000	0.029	0.032	0.054	0.075	0.079
Mill Rate	0.000	0.000	0.241	-0.001	-0.001	0.000	0.000	0.000
Pollution	0.000	0.001	0.264	-0.001	-0.001	0.000	0.001	0.001
Racial Fract	-0.249	0.019	0.000	-0.285	-0.280	-0.248	-0.218	-0.211
Income	0.001	0.000	0.000	0.001	0.001	0.001	0.001	0.001
Crime	-0.138	0.029	0.000	-0.195	-0.186	-0.138	-0.091	-0.083
$\rho$	0.561	0.007	0.000	0.547	0.549	0.561	0.571	0.574

Spatial weight matrix is row-stochastic and based on 6 nearest neighbors and prior r-value of 8. Sample size is 16,020 and Gibbs sampling procedure used 5,000 draws following 500 omissions. The model carried an  $\bar{R}^2 = 0.72$ .



Table 2.6: Columbus Bayesian Spatial AR Linear Regression Posterior Estimates of Model II

<b>Dep: ln(hprice)</b>	$\mu$	$\sigma$	p-value	$\beta^{.025}$	$\beta^{.05}$	$\beta^{.5}$	$\beta^{.95}$	$\beta^{.975}$
Intercept	4.088	0.081	0.000	3.933	3.954	4.088	4.224	4.247
House Size	0.274	0.010	0.000	0.256	0.258	0.274	0.289	0.292
House Size <sup>2</sup>	-0.007	0.002	0.000	-0.011	-0.010	-0.007	-0.004	-0.003
ln(Yard Size)	0.084	0.004	0.000	0.076	0.078	0.084	0.090	0.091
W-House Size	-0.113	0.007	0.000	-0.126	-0.124	-0.113	-0.102	-0.099
W-ln(Yard Size)	-0.079	0.006	0.000	-0.091	-0.089	-0.079	-0.069	-0.067
Maximum House	-0.020	0.011	0.043	-0.042	-0.039	-0.020	-0.001	0.002
One Story	0.010	0.004	0.004	0.003	0.004	0.010	0.016	0.017
W-OneStory	0.044	0.006	0.000	0.031	0.033	0.044	0.054	0.056
Air	0.049	0.004	0.000	0.041	0.042	0.049	0.056	0.057
W-Air	0.011	0.006	0.034	-0.001	0.001	0.011	0.020	0.022
Fire	0.031	0.003	0.000	0.026	0.027	0.031	0.036	0.037
W-Fire	0.010	0.005	0.027	0.000	0.001	0.010	0.018	0.020
Full Baths	0.060	0.003	0.000	0.054	0.055	0.060	0.066	0.067
Part Baths	0.027	0.003	0.000	0.020	0.021	0.027	0.032	0.033
W-Bath	0.014	0.005	0.004	0.003	0.005	0.014	0.023	0.025
Age	-0.656	0.029	0.000	-0.713	-0.704	-0.656	-0.607	-0.597
Age <sup>2</sup>	0.354	0.022	0.000	0.312	0.319	0.353	0.390	0.397
W-Age	0.359	0.035	0.000	0.291	0.301	0.359	0.415	0.426
W-Age <sup>2</sup>	-0.040	0.027	0.073	-0.092	-0.084	-0.040	0.005	0.014
Deck	0.021	0.012	0.036	-0.002	0.002	0.021	0.041	0.044
W-Deck	0.032	0.023	0.081	-0.013	-0.007	0.032	0.070	0.078
Proficiency	0.001	0.000	0.000	0.001	0.001	0.001	0.002	0.002
Per Pupil Sending	0.016	0.002	0.000	0.013	0.014	0.016	0.019	0.020
Mill Rate	0.000	0.000	0.487	-0.001	-0.001	0.000	0.001	0.001
Pollution	-0.001	0.001	0.079	-0.002	-0.001	-0.001	0.000	0.000
Racial Fract	-0.164	0.017	0.000	-0.197	-0.192	-0.164	-0.137	-0.132
Income	0.001	0.000	0.000	0.001	0.001	0.001	0.001	0.001
Crime	-0.081	0.026	0.001	-0.132	-0.124	-0.081	-0.037	-0.029
$\rho$	0.598	0.007	0.000	0.585	0.587	0.598	0.609	0.611

Spatial weight matrix is row-stochastic and based on 6 nearest neighbors and prior r-value of 3. Sample size is 16,020 and Gibbs sampling procedure used 5,000 draws following 500 omissions. The model carried an  $\bar{R}^2 = 0.74$ .

Table 2.7: Cleveland Bayesian Spatial AR Linear Regression Posterior Estimates of Model I

<b>Dep: ln(hprice)</b>	$\mu$	$\sigma$	p-value	$\beta^{.025}$	$\beta^{.05}$	$\beta^{.5}$	$\beta^{.95}$	$\beta^{.975}$
Intercept	6.863	0.116	0.000	6.634	6.674	6.861	7.056	7.089
House Size	0.284	0.007	0.000	0.270	0.272	0.284	0.295	0.297
House Size <sup>2</sup>	-0.007	0.000	0.000	-0.008	-0.008	-0.007	-0.007	-0.007
ln(Yard Size)	0.079	0.006	0.000	0.068	0.070	0.079	0.088	0.090
W-House Size	-0.047	0.008	0.000	-0.062	-0.060	-0.047	-0.034	-0.031
W-ln(Yard Size)	-0.058	0.008	0.000	-0.073	-0.070	-0.058	-0.045	-0.042
Maximum House	-0.055	0.034	0.051	-0.120	-0.110	-0.055	0.001	0.012
One Story	-0.012	0.006	0.019	-0.024	-0.021	-0.012	-0.002	-0.001
Air	0.013	0.007	0.029	0.000	0.002	0.013	0.024	0.026
Fire	0.052	0.005	0.000	0.043	0.044	0.052	0.060	0.061
Full Baths	0.049	0.006	0.000	0.038	0.040	0.049	0.059	0.060
Part Baths	0.057	0.005	0.000	0.047	0.048	0.057	0.065	0.067
Age	-0.207	0.032	0.000	-0.270	-0.260	-0.207	-0.154	-0.145
Age <sup>2</sup>	0.006	0.023	0.400	-0.039	-0.032	0.006	0.044	0.052
Deck	0.046	0.007	0.000	0.033	0.035	0.046	0.057	0.059
Proficiency	0.003	0.000	0.000	0.002	0.002	0.003	0.003	0.003
Per Pupil Sending	-0.006	0.002	0.006	-0.010	-0.010	-0.006	-0.002	-0.001
Mill Rate	0.001	0.000	0.000	0.001	0.001	0.001	0.002	0.002
Pollution	0.000	0.002	0.419	-0.004	-0.004	0.000	0.003	0.004
Racial Fract	-0.154	0.015	0.000	-0.184	-0.179	-0.154	-0.130	-0.125
Income	0.002	0.000	0.000	0.002	0.002	0.002	0.002	0.002
Crime	-0.011	0.068	0.438	-0.142	-0.121	-0.011	0.101	0.124
$\rho$	0.360	0.010	0.000	0.341	0.343	0.360	0.377	0.380

Spatial weight matrix is row-stochastic and based on 5 nearest neighbors and prior r-value of 30. Sample size is 11,871 and Gibbs sampling procedure used 5,000 draws following 500 omissions. The model carried an  $\bar{R}^2 = 0.75$ .

Table 2.8: Cleveland Bayesian Spatial AR Linear Regression Posterior Estimates of Model II

<b>Dep: ln(hprice)</b>	$\mu$	$\sigma$	p-value	$\beta^{.025}$	$\beta^{.05}$	$\beta^{.5}$	$\beta^{.95}$	$\beta^{.975}$
Intercept	6.853	0.126	0.000	6.603	6.646	6.854	7.062	7.097
House Size	0.269	0.007	0.000	0.256	0.258	0.269	0.281	0.283
House Size <sup>2</sup>	-0.007	0.000	0.000	-0.008	-0.008	-0.007	-0.007	-0.006
ln(Yard Size)	0.087	0.006	0.000	0.076	0.078	0.087	0.096	0.098
W-House Size	-0.033	0.010	0.001	-0.053	-0.050	-0.033	-0.017	-0.014
W-ln(Yard Size)	-0.062	0.008	0.000	-0.077	-0.075	-0.062	-0.049	-0.047
Maximum House	-0.050	0.034	0.074	-0.117	-0.106	-0.050	0.006	0.017
One Story	-0.018	0.007	0.005	-0.031	-0.029	-0.018	-0.007	-0.005
W-OneStory	0.019	0.011	0.042	-0.003	0.001	0.019	0.037	0.040
Air	0.021	0.007	0.002	0.007	0.009	0.021	0.033	0.035
W-Air	-0.024	0.013	0.026	-0.049	-0.045	-0.024	-0.004	0.000
Fire	0.049	0.005	0.000	0.039	0.041	0.049	0.057	0.058
W-Fire	0.037	0.009	0.000	0.019	0.022	0.038	0.053	0.055
Full Baths	0.043	0.006	0.000	0.032	0.034	0.043	0.053	0.055
Part Baths	0.051	0.005	0.000	0.041	0.043	0.051	0.060	0.062
W-Bath	0.022	0.008	0.005	0.006	0.008	0.022	0.036	0.038
Age	-0.602	0.041	0.000	-0.680	-0.668	-0.602	-0.534	-0.522
Age <sup>2</sup>	0.264	0.029	0.000	0.208	0.216	0.264	0.311	0.319
W-Age	0.850	0.056	0.000	0.741	0.757	0.850	0.941	0.960
W-Age <sup>2</sup>	-0.569	0.040	0.000	-0.647	-0.635	-0.569	-0.503	-0.489
Deck	0.040	0.007	0.000	0.027	0.029	0.040	0.051	0.054
W-Deck	0.039	0.015	0.007	0.009	0.014	0.039	0.064	0.069
Proficiency	0.003	0.000	0.000	0.002	0.002	0.003	0.003	0.003
Per Pupil Sending	-0.015	0.002	0.000	-0.019	-0.019	-0.015	-0.011	-0.010
Mill Rate	0.000	0.000	0.404	-0.001	-0.001	0.000	0.000	0.001
Pollution	0.001	0.002	0.336	-0.003	-0.002	0.001	0.004	0.005
Racial Fract	-0.120	0.015	0.000	-0.151	-0.146	-0.120	-0.095	-0.090
Income	0.002	0.000	0.000	0.001	0.001	0.002	0.002	0.002
Crime	-0.045	0.072	0.266	-0.186	-0.162	-0.045	0.071	0.096
$\rho$	0.354	0.011	0.000	0.333	0.337	0.354	0.371	0.375

Spatial weight matrix is row-stochastic and based on 5 nearest neighbors and prior r-value of 30. Sample size is 11,871 and Gibbs sampling procedure used 5,000 draws following 500 omissions. The model carried an  $\bar{R}^2 = 0.76$ .

Table 2.9: Cincinnati Bayesian Spatial AR Linear Regression Posterior Estimates of Model I

Dep: ln(hprice)	$\mu$	$\sigma$	p-value	$\beta^{.025}$	$\beta^{.05}$	$\beta^{.5}$	$\beta^{.95}$	$\beta^{.975}$
Intercept	5.765	0.091	0.000	5.583	5.616	5.765	5.911	5.944
House Size	0.325	0.011	0.000	0.302	0.306	0.325	0.343	0.347
House Size <sup>2</sup>	-0.009	0.002	0.000	-0.013	-0.012	-0.009	-0.006	-0.006
ln(Yard Size)	0.075	0.004	0.000	0.066	0.067	0.075	0.081	0.083
W-House Size	-0.059	0.007	0.000	-0.074	-0.072	-0.059	-0.047	-0.045
W-ln(Yard Size)	-0.080	0.006	0.000	-0.093	-0.091	-0.080	-0.070	-0.068
Maximum House	-0.035	0.023	0.063	-0.081	-0.073	-0.035	0.003	0.010
One Story	0.025	0.005	0.000	0.015	0.017	0.025	0.034	0.036
Air	0.025	0.006	0.000	0.013	0.015	0.026	0.035	0.037
Fire	0.071	0.004	0.000	0.063	0.064	0.071	0.078	0.079
Full Baths	0.032	0.005	0.000	0.023	0.024	0.032	0.039	0.041
Part Baths	0.029	0.005	0.000	0.020	0.021	0.029	0.036	0.038
Age	-0.133	0.026	0.000	-0.184	-0.175	-0.133	-0.088	-0.079
Age <sup>2</sup>	-0.029	0.023	0.098	-0.074	-0.067	-0.029	0.009	0.015
Deck	0.060	0.005	0.000	0.049	0.051	0.060	0.069	0.070
Proficiency	0.002	0.000	0.000	0.002	0.002	0.002	0.003	0.003
Per Pupil Sending	0.033	0.002	0.000	0.029	0.030	0.033	0.037	0.038
Mill Rate	0.000	0.000	0.369	-0.001	-0.001	0.000	0.001	0.001
Pollution	-0.004	0.001	0.000	-0.006	-0.005	-0.004	-0.002	-0.002
Racial Fract	-0.319	0.028	0.000	-0.376	-0.366	-0.318	-0.271	-0.263
Income	0.002	0.000	0.000	0.002	0.002	0.002	0.002	0.002
Crime	0.064	0.084	0.220	-0.107	-0.078	0.064	0.202	0.226
$\rho$	0.443	0.008	0.000	0.427	0.430	0.443	0.456	0.458

Spatial weight matrix is row-stochastic and based on 4 nearest neighbors and prior r-value of 8. Sample size is 13,115 and Gibbs sampling procedure used 5,000 draws following 500 omissions. The model carried an  $\bar{R}^2 = 0.54$ .

Table 2.10: Cincinnati Bayesian Spatial AR Linear Regression Posterior Estimates of Model II

<b>Dep: ln(hprice)</b>	$\mu$	$\sigma$	p-value	$\beta^{.025}$	$\beta^{.05}$	$\beta^{.5}$	$\beta^{.95}$	$\beta^{.975}$
Intercept	6.075	0.099	0.000	5.882	5.913	6.073	6.241	6.272
House Size	0.308	0.011	0.000	0.285	0.289	0.308	0.326	0.330
House Size <sup>2</sup>	-0.010	0.002	0.000	-0.014	-0.013	-0.010	-0.007	-0.006
ln(Yard Size)	0.088	0.004	0.000	0.079	0.080	0.088	0.095	0.096
W-House Size	-0.010	0.009	0.130	-0.028	-0.025	-0.011	0.005	0.008
W-ln(Yard Size)	-0.107	0.007	0.000	-0.120	-0.118	-0.107	-0.096	-0.093
Maximum House	-0.021	0.023	0.180	-0.066	-0.058	-0.021	0.017	0.024
One Story	0.015	0.006	0.002	0.004	0.006	0.015	0.024	0.026
W-OneStory	0.052	0.010	0.000	0.033	0.036	0.052	0.069	0.072
Air	0.036	0.011	0.000	0.015	0.018	0.036	0.053	0.057
W-Air	0.020	0.013	0.058	-0.005	-0.001	0.020	0.042	0.045
Fire	0.062	0.005	0.000	0.053	0.055	0.062	0.070	0.071
W-Fire	0.080	0.009	0.000	0.063	0.065	0.080	0.094	0.097
Full Baths	0.034	0.005	0.000	0.025	0.026	0.034	0.042	0.044
Part Baths	0.032	0.005	0.000	0.023	0.024	0.032	0.040	0.041
W-Bath	-0.009	0.007	0.093	-0.023	-0.021	-0.009	0.002	0.004
Age	-0.593	0.037	0.000	-0.665	-0.653	-0.593	-0.531	-0.519
Age <sup>2</sup>	0.236	0.029	0.000	0.178	0.189	0.236	0.285	0.294
W-Age	0.744	0.050	0.000	0.644	0.660	0.743	0.827	0.840
W-Age <sup>2</sup>	-0.435	0.042	0.000	-0.515	-0.503	-0.435	-0.367	-0.353
Deck	0.044	0.006	0.000	0.033	0.034	0.043	0.053	0.055
W-Deck	0.104	0.011	0.000	0.082	0.085	0.104	0.122	0.125
Proficiency	0.002	0.000	0.000	0.002	0.002	0.002	0.003	0.003
Per Pupil Sending	0.022	0.002	0.000	0.018	0.019	0.022	0.026	0.026
Mill Rate	-0.001	0.000	0.045	-0.002	-0.001	-0.001	0.000	0.000
Pollution	-0.004	0.001	0.000	-0.006	-0.006	-0.004	-0.002	-0.002
Racial Fract	-0.281	0.029	0.000	-0.340	-0.330	-0.281	-0.233	-0.225
Income	0.002	0.000	0.000	0.002	0.002	0.002	0.002	0.002
Crime	0.062	0.085	0.231	-0.103	-0.078	0.060	0.203	0.230
$\rho$	0.419	0.008	0.000	0.403	0.405	0.419	0.433	0.435

Spatial weight matrix is row-stochastic and based on 4 nearest neighbors and prior r-value of 10. Sample size is 13,115 and Gibbs sampling procedure used 5,000 draws following 500 omissions. The model carried an  $\bar{R}^2 = 0.57$ .

of 0.287 for a 1,000 square foot increase in the housing size. An increase in the average size of neighboring houses by 1,000 feet, however, reduces the price by -0.105 percent on average, with a 95% credibility interval between -0.117 and -0.092. The sign of this effect is consistent with the expectations of the relative status literature, as summarized in Table 2.4. However, the magnitude of the relative effect is only about one-third of the absolute effect. It would seem to imply that if neighbors were to get into a relative status “arms race,” that the net effect is not a zero-sum game but positive.

Elsewhere in Table 2.5, yard size better fits the story of a zero-sum game where an increase in the size of the average yard of neighboring properties lowers the value of a property by about the same amount as an increase in the size of its own yard. There are several ways this might be interpreted.<sup>7</sup> It is interesting this result appears, as zoning laws often limit a minimum lot size, whereas if neighborhoods were prone to zero-sum games of expanding territory you might expect they would use the local zoning laws to undermine this propensity, in which case maximum lot sizes would be the norm.<sup>8</sup> It could be that yard size is actually serving as a proxy variable for how physically close one house is to another. Perhaps structures sitting on very small lots are more likely to be closer to the edge of another owner’s property, and this is negatively reflected in observed sale prices.

Another interesting result in Table 2.5 is that the realtor adage to “never buy the largest house on the block” carries weight with buyers. If a house is the largest of the neighbors in the spatial weight matrix, then it sells for a discount of about -0.034 percent on average. This would seem to run against the relative status literature, where if people valued owning a house larger than their neighbors, regardless of its absolute size, that they would be selling for a premium to reflect the greater utility.

Model II expands Model I by including the spatial lags of the other house-specific control

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<sup>7</sup>The quadratic effect of yard size tended to be multicollinear with the house size characteristics, so it was excluded.

<sup>8</sup>It is likely that some areas do have maximum lot sizes for residential housing, but our observation is that these types of requirements are more commonly employed over mobile home property rather than owner-occupied detached housing units.

variables, rather than just house and yard size. For instance, if the neighbors have fireplaces, air condition, the age of their housing, or a deck, etc. The Columbus dataset is estimated for Model II and presented in Table 2.6. The primary consequence this has on the coefficients is to lower the estimates of the own-house size and increase the magnitude of the relative status effect. Whereas in Model I, the absolute effect was about three times larger than the relative effect, in Model II it is only about two and a half times larger. Still, the offsetting effects between own-yard size and neighboring yard sizes are fairly close, though at the mean own-yard size is now slightly larger. Furthermore, the discount at which the “largest house on the block” sells at diminishes from the previous estimates.

The remaining spatial lags of the independent variables suggests that there is a positive correlation between the sale price of a house and the amount of amenities the neighboring homes have. These neighboring amenities include having central air, a fire place, full baths, and a deck. The other characteristics are not particularly clear as to what direction the sign should be under the relative status hypothesis. The expected value for the home being a single story is positive, as it is when the neighbor is a single-story. This may actually be picking up certain neighborhoods around Columbus that are further away from the city.

The other neighborhood control variables generally behave as expected in Table 2.6. Census block median income, proficiency scores, and per pupil expenditures are positively correlated with housing prices, while the crime rate, pollution, and degree of racial fractionalization have a negative effect.

Cleveland results are presented in Tables 2.7 and 2.8, and the Cincinnati results are presented in Tables 2.9 and 2.10. While differing somewhat in magnitude from the Columbus results, they carry the same qualitative results. The relative size of a housing unit matters in all cases but is considerably weaker than the absolute size. Furthermore, when the model is expanded to include the spatial lags of other housing characteristics besides size and yard, this difference shrinks as the relative size coefficient becomes larger (in absolute value) and the absolute size coefficient lowers. Yard and neighboring yard size are about off-setting in

each estimation when both are increased in equal amounts. When a house is larger than the neighbors in the spatial weight matrix, that house sells for a discount in all estimations. The notable exception is that in Table 2.10, the effect is negative on average but only 82 percent of the distribution is negative.

To put the estimates into a more quantifiable context, I use the Model II estimates presented in Table 2.6, 2.8, and 2.10 to calculate the total mean marginal change in willingness-to-pay for a change in an independent variable. Since the interest is in determining the net effect of absolute and relative changes in characteristics, the most informative calculation would be to estimate the total impact on the mean house price that would result from changing explanatory variable  $k$  by the same amount across all observations. Intuitively, this would be like asking, “what would happen to observation  $i$ ’s price if every house in the MSA increased by 100 square feet?”<sup>9</sup>

The results of the calculations are presented in Table 3.15, which provides the total effect as well as the intermediate calculations for the absolute and relative effects. For Columbus, the estimates suggest that if everyone were to increase the size of their house by 100 square feet, the total average impact would be to increase the mean house price by 0.38 percent, which is about \$559. As it can be seen, when an house increases its own size by 100 feet, the absolute effect was to increase the value of the home by \$968, but the relative status effect of everyone else increasing their house size by 100 feet resulted in a -\$410 decline. By stark contrast, if every house were to expand its yard size by 100 feet, the total average effect would be to increase the value of the mean house price by \$18. The most staggering effect is the discount to those purchasing the largest house among the neighbors, a five percent discount worth just over \$7,000. These Columbus results do not differ considerably when comparing to Cleveland and Cincinnati.

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<sup>9</sup>Willingness to pay is calculated by  $\Delta x_j \beta_j (\frac{1}{1-\rho}) \bar{y}$  following Kim et al. (2003b).



Table 2.11: Mean Marginal Changes in Willingness-to-Pay

Variable ( $\Delta x_j$ )	Columbus		Cleveland		Cincinnati	
	MWP (\$)	% Change	MWP (\$)	% Change	MWP (\$)	% Change
Own House Size ( $\Delta 100sqft$ )	994	0.68	548	0.42	747	0.53
Own House Size <sup>2</sup> ( $\Delta 100sqft$ )	-26	-0.02	-14	-0.01	-25	-0.02
Own Yard Size ( $\Delta .01$ Acres)	304	0.21	177	0.13	213	0.15
W-House Size ( $\Delta 100sqft$ )	-410	-0.28	-68	-0.05	-25	-0.02
W-Yard Size ( $\Delta .01$ Acres)	-286	-0.20	-127	-0.10	-260	-0.18
Maximum House ( $0 \rightarrow 1$ )	-7,330	-5.03	-10,123	-7.70	-5,022	-3.56
Total - $\Delta$ House Size	559	0.38	466	0.35	697	0.49
Total - $\Delta$ Yard Size	18	0.01	50	0.04	-47	-0.03

Note: Calculations based on an increase in own house size of 100sqft from the mean and neighbors' house size effects are calculated based on a decrease in size of the average neighbors house by 100sqft from the mean.

## 5 Conclusion

This chapter has estimated the effect of absolute status and relative status on housing prices with status being proxied by housing size. The evidence provided here suggests that individuals do care about both relative and absolute status. However, an increase in absolute house size is valued much more than an increase in relative house size, suggesting that individuals value their absolute status more than their relative status. With respect to the housing market, our results offer a estimate supporting the well-known adage in real estate to never buy the largest house on the block. Our methodology allows us to control for the possibility that a smaller house may enjoy positive spatial spillovers from neighboring houses, and instead focus on the isolated effect of relative size.

With regards to policy, this result suggests that policies which increase relative income may be welfare enhancing but not if it comes at the expense of absolute income (assuming the changes are equivalent). In other words, redistribution may increase general welfare but only if the cost is not a decline in absolute income levels on average. Survey data literature agrees with the direction of preference for relative status, but diverges with respect to magnitude,

often drawing the conclusion that relative status matters more. This conclusion would suggest that redistribution to some extent may be welfare enhancing even if it lowers absolute income. Our results suggest the opposite, that lowering absolute consumption in favor of relative consumption is welfare reducing.

The inability of survey data analysis to accurately capture the magnitude of preferences makes the method an unattractive substitute for a revealed preference approach. While survey data does allow economists to ask interesting questions, the usefulness of the answers must be constrained to direction, not strength. Given the increasing reliance on survey data for policy recommendations, there is a great deal of research left to be done regarding the verification of conclusions drawn from such methods. In the next chapter I will allow for the possibility that other neighbor groups may influence house price.

# Chapter 3

## The Influence of Reference Group

### House Size on House Price

“A house may be large or small; as long as the surrounding houses are equally small it satisfies all social demands for a dwelling. But if a palace rises beside the little house, the little house shrinks into a hut.”

*(Karl Marx)*

#### 1 Introduction

Karl Marx’s observation highlights the tendency of individuals to view the value of their possessions in relative terms. Veblen (1899) first coined the term “conspicuous consumption” to describe the idea that individuals value their relative consumption level in addition to their absolute. Conspicuous consumption has also been referred to as “envy” (Eaton and Eswaran, 2003), where the consumption of others negatively affects one’s utility, *ceteris paribus* and the increase in relative consumption positively affects one’s utility.

Housing is a particularly powerful symbol of status and prestige (Sadalla et al., 1987; Belk et al., 1982; Coleman and Rainwater, 1978; Felson, 1978; Duncan and Duncan, 1978; Cooper, 1974, 1972; Katona, 1964), which, according to the conspicuous consumption hypothesis,

leads to a desire for a relatively larger house. In a race to convey the highest status, the desire for relatively large houses leads to building larger houses and “when everyone builds bigger, the primary effect is merely to raise the bar that defines the size of home that people feel they need” (Frank, 2009) without increasing the utility of anyone. If indeed this preference for relative size is evident, we should observe that housing prices are negatively affected by an increase in the housing consumption of others.

However, it may also be that individuals indirectly gain from an increase in others’ housing consumption. Individuals have been shown to publicize or emphasize connections with successful individuals through a behavior known as ‘basking in the reflected glory’ (BIRG) (Cialdini et al., 1976). Consumption levels have historically acted as a perceived proxy for success (Podolny, 2005) and consequently, individuals may value high consumption of those with whom they share a connection because they may be perceived as successful by proxy. This tendency lies in opposition to the desire for relative status because now an individual gains through association with higher consuming individuals, even though the success of that group decreases the individual’s relative status. While individuals may still envy or desire relative status with respect to those with whom they are associated, it is now the case that the reflected glory of consumption has a greater effect than the desire for relative status.

The magnitude of influence of envy and/or reflected glory likely depends on the social reference group of the individual. Schor (1998) discusses the formation of reference groups and how the relationship of an individual to a given social reference group changes consumption patterns. In addition to social groups, the perceived closeness of an individual to a given group is largely thought to determine reference groups (Layard, 2003; Pleban and Tesser, 1981) but little discussion of particular reference groups exists in the economic literature (Amiel and Cowell, 1999; Kulik and Ambrose, 1992). Housing lends itself very neatly to spatially determined reference groups and is also a highly visible form of consumption. As such, the housing sector is an excellent market to study spatially determined reference group association and relative consumption influences.

This chapter explores the effect of a change in the housing consumption of various reference groups on predicted house price. I use a spatial autoregressive hedonic model to examine change in predicted house price associated with a change in house size of four different reference groups: nearest neighbors, surrounding neighborhoods, the largest houses in the district and the smallest houses in the district. If an increase in average house size of the given reference group is associated with a decrease predicted house price, it suggests that the envy effect dominates the relationship. On the other hand, if an increase in the average house size of the given reference group is associated with an increase predicted house price, this suggests that the reflected glory effect dominates. In addition to isolating the associated effect of a change in relative house size on predicted house price for different reference groups, this paper also contributes via methodology. Extending the application of spatial hedonic models expands the potential of applying such methods to new research fields as well as reinforcing the importance of accounting for spatial dependence. The remainder of the paper is organized as follows. Section 2 reviews the literature, section 3 describes the methodology and data employed, section 4 presents the results and section 5 concludes.

## **2 Literature Review**

### **2.1 Envy, Reflected Glory and Reference Groups**

In broad terms “envy” implies that individuals experience disutility from having less than their peers (Zizzo, 2007). An increase in the consumption of an individual’s peers, all other things equal, has a negative effect on utility while a decrease in peers’ consumption has a positive effect on utility. In this context, conspicuous consumption may be thought of as consuming highly visible status goods to gain relative status, in part, through invoking envy of others.

Apart from the utility derived from invoking envy of others (or responding to envy felt of another’s consumption), signaling higher status through consumption of goods has noted

benefits. It has been found that individuals who consume goods that symbolize status or prestige are treated more favorably; automobiles (Munson and Austin, 1980; Doob and Gross, 1968; Grubb and Hupp, 1968; Wells et al., 1957) and clothing (Holman, 1980; Bickman, 1971; Douty, 1963) have been shown to be status goods which affect the treatment of the consumer by others. Relative increases in consumption of status goods increases perceived status, to the detriment of those who now are consuming relatively less. As previously noted, housing is a very strong symbol of status (Sadalla et al., 1987; Belk et al., 1982; Coleman and Rainwater, 1978; Felson, 1978; Duncan and Duncan, 1978; Cooper, 1974, 1972; Katona, 1964) and, as such, we would expect to see evidence of the preference for relative status in the housing market. If true, this implies that individuals would rather live in a given house surrounded by smaller reference group houses than that same house surrounded by larger reference group houses.

Conversely, individuals have also been shown to ‘bask in the reflected glory’(BIRG) of others who are, or appear to be, successful. To ‘BIRG’ was originally coined by Cialdini et al. (1976), when he demonstrated university students’ propensity to wear school-identifying apparel after the sports teams won games. Since then, evidence of ‘BIRG’ has been seen with respect to politics (Boen et al., 2002), academic achievement (Marsh, 1986) and self esteem (Tesser, 1988). For housing, if individuals do ‘BIRG’, this would imply individuals prefer their neighbors’ to increase their housing consumption (and consequently their perceived status), even though the individual’s relative housing consumption has declined as a result. That is, individuals may prefer to live in an area with extremely large houses, even though this would make their house relatively smaller.

The relationship of the individual to any given reference group will likely influence which effect dominates. Hyman et al. (1954) first noted that reference groups serve as points of comparison and the effect of status changes with reference groups. Given this, it may be that individuals experience disutility with an increase in consumption of some reference groups (envy), while experiencing gains in utility from increased consumption of a different reference

group (reflected glory). The spatial proximity of the reference group would intuitively play an important role in the strength of the relationship.<sup>1</sup>

Regarding reference groups for housing consumption, the nearest neighbors of an individual are the most observable influences on consumption. Driving in and out of the neighborhood provides a daily reminder of housing consumption of the closest neighbors. Leguizamon and Ross (2008) found that with respect to nearest neighbors, an increase in the average house size of the nearest neighbors decreased the predicted house price. However, nearest neighbors are only one of potentially numerous reference groups. Surrounding neighborhoods also play an important role. School, police, and fire districts as well as other public good provisions such as parks and recreation facilities are comprised of several neighborhoods within a given area. Interaction of individuals within public good consumption environments may provide fodder for comparison as well, through school activities, volunteer organizations and other community endeavors. Other potential influential reference groups include individuals at the extreme consumption levels. It has been suggested that individuals “compare up” when making relative consumption comparisons (Russell, 1930). That is, individuals are comparing themselves to the highest consuming individuals within the group (in this case within a given housing district). Incorporating the predicted change associated with a change in house size of the largest houses in the district will isolate this reference group effect. Similarly, we can also observe if individuals are influenced by changes in housing consumption of the neighbors in the smallest houses for a given district.

As previously noted, evidence for the domination of the envy effect has been found for nearest neighbors. As such, we would expect results consistent with that conclusion. James (1987) found that internationally, poor countries tended to compare themselves to the richest countries. Consequently, we might expect that the envy effect will dominate when considering the highest consuming reference group (the richest, or largest, houses in the district); however, anecdotal experience suggests the result could go either way when

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<sup>1</sup>Social network reference groups arguably have a larger impact on consumption than spatially formed groups but are not included in the current data set and are left for future research.

considering housing in particular. It is easy to imagine individuals desiring to have a house that is close in size to the largest houses in the city or district, but it is also easy to imagine individuals gaining utility from being associated with individuals who can afford much larger houses. A subdivision of McMansions may make your previously relatively large house feel less valuable due to the loss in relative status, or it may make it feel more valuable by simply living close to individuals who live in McMansions.

Regarding the smallest houses in the district, Daly and Wilson (2006) found individuals exhibit a preference for “staying ahead of the Smiths” (where the Smiths are those who are relatively poor) with respect to income. If this is true with housing consumption as well, a decrease in the size of the smallest, or poorest, houses will make own house feel even larger by comparison (will increase the distance from the Smiths), and will be associated with an increase in predicted house price. On the other hand, it may be that a decrease in the size of the smallest houses increases any negative connotation of the area that outweighs the value from an increase in relative house size (individuals now experience an association with an increasingly undesirable reference group). However, we may also observe this outcome if individuals exhibit empathy towards the relatively poor and consequently do not value an increase in relative house size with respect the smallest houses in the district.

Concerning neighborhoods surrounding own house (not on own street but within the district) we may observe envy (if the group is considered consumption competition) or reflected glory (if individuals value increased consumption by association). For all cases, it may also be that the consumption of housing for any given reference group has no effect on predicted own house price. Individuals may not influenced one way or the other by the house sizes of the different reference groups in question.

Turnbull et al. (2006) previously explored the influence of relative size on housing price, testing three theories of relative size. The first is the atypical housing effect, proposed by Haurin (1988), which suggests houses with atypical features (such as being larger or smaller than other houses in the neighborhood) will sell at a discount. The second theory is the



notion of conspicuous consumption, attributable to Veblen (1899) and later to Leibenstein (1950), which suggests individuals value consuming more than those around them. This implies houses larger than the surrounding houses will sell at a premium. The third is the “tax capitalization effect” (Hamilton, 1976) which suggests larger houses bear a greater proportion of public good costs through higher property taxes. This theory predicts smaller houses will sell at a premium and larger houses will sell at a discount. Turnbull et al. (2006) found that indeed, smaller houses sell at a premium and larger houses sell at a discount, supporting the tax capitalization explanation. They used a 2SLS procedure to estimate the effects of relative house size of neighbors within 0.5 miles for approximately 2200 observations. This paper reexamines this issue by employing a spatial autoregressive model to estimate the results for 16,000 observations from a different locale. Through the use of spatial models, as well as a larger data set, I am able to discriminate between the effect of different neighbor groups and thus test for outcomes Turnbull et al. (2006) could not.<sup>2</sup>

## 2.2 Hedonic Model with Spatial Spillovers

Hedonic analysis is a well established method of extracting prices for non-market goods through revealed preferences. Hedonic theory postulates that the price of a house represents the price of a bundle of goods, or characteristics. The aggregate implied prices of all housing characteristics is the price of the house (Rosen, 1974). Hedonic models have been used to estimate the relationship between house price and hazardous waste sites (Hite et al., 2001; Kohlhase, 1991; Nelson et al., 1992), environmental quality (Brasington and Hite, 2003), air pollution (Kim et al., 2003a; Beron and J. Murdoch, 2001; Chattopadhyay, 1999; Kiel and McClain, 1995; Smith and Deyak, 1975) and water pollution (Hoehn et al., 1987).

A higher willingness to pay for certain housing characteristics, measured by a change

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<sup>2</sup>The use of the spatial autoregressive model rather than a 2SLS procedure (with dummy variables to control for location effects) allows for spatial spillovers between divisions to occur rather than assuming there is no spatial interaction between neighbors in different subdivisions or MLS areas. The spatial autoregressive model is discussed in further depth in Section 2.2 and 3.2.

in the predicted price of the house, suggests an individual's greater preference for that characteristic. For example, if the shadow price of an extra bathroom on a given house is less than the shadow price of an extra bedroom on that same house, *ceteris paribus*, this implies that individuals in the market place more value on the additional bedroom than the additional bathroom. Similarly if an increase in the house size of any given reference group is associated with a decreased predicted house price, individuals may prefer the reference group to have a lower housing consumption level.

Some characteristics affect the price of a given house through two different channels, the direct effect and the indirect effect through spatial spillovers. The direct effect carries the traditional beta coefficient interpretation. Spatial spillovers can occur when the effect of a change in a characteristic on one observation of the dependent variable triggers a change in other observations of the dependent variable, which have an additional effect on the original observation. In the housing market, for instance, adding a deck will increase the price of the house. An increase in the price of a house will increase the price of the neighbor's house. When the neighbor's house increases in price, this will increase the price of the original house even more. These spatial spillovers have been shown to be significant in hedonic markets (Brasington and Hite, 2003) and are increasingly incorporated via a spatial weight matrix. Recently, (Lacombe, 2004a) has extended the use of these spatial weight matrices to compare different subsets of groups, and consequently different weighted matrices, simultaneously. This paper will examine the willingness to pay for relative housing consumption of different reference groups, using an approach similar to Lacombe (2004a), applied to hedonic markets in the same vein as Brasington and Hite (2003).

## 3 Methodology and Data

### 3.1 Data

The Brasington Housing Data Set is employed. A description of the data and a summary of statistics can be found in Chapter 2. As previously assumed, housing price is assumed to be a function of school quality (Brasington, 1999), environmental quality (Brasington and Hite, 2003), the tax rate, the degree of racial fractionalization, crime level and physical house amenities. Physical amenities include the presence of a deck, air conditioning, number of stories, number of bathrooms, yard size, age of house and, the variable of interest, size of house. The physical amenities (bedrooms, bathrooms, etc) are house specific by X-Y coordinates and neighborhood characteristics (air quality, school quality, etc) represent the average of the census group to which the house belongs. School quality is measured by proficiency test scores relative to average proficiency test scores for each MSA and environmental quality is measured by hazardous air emissions per ton. Following the literature, it is predicted that all physical housing amenities, excluding age of house and tax rate, have a positive effect while degree of racial fractionalization, crime rate and air emissions per ton have a negative effect. Age of the house could be negative if it requires expensive upkeep or positive if it has historical appeal. Tax rate may be negative because of the cost or positive if it acts as a proxy for public good provision.

The subset of independent variables chosen to control for changes in the housing characteristics of the closest neighbors are the general characteristics of the neighborhood. Similarly, the size of the neighbor's house, the age of the neighbor's house and neighbor's yard size are included in the regression. Other physical neighbor house characteristics are unobservable from the street (deck, number of bathrooms, etc) and consequently a change is assumed not to affect house price. Any other spatial correlation is captured in  $\rho$ . The only independent variable included for further neighbors is housing size, the variable of interest. All other effects are captured in the spatial lag of  $\rho$ .

## 3.2 Methodology

General hedonic models are described as follows:

$$v = \beta\chi + \varepsilon; \tag{3.1}$$

where  $\chi$  is the vector of explanatory variables,  $v$  is the price of the house and  $\varepsilon$  is normally distributed with a zero mean. However, when spatial correlation between observations exists, OLS will be biased and inconsistent. Typically, there are two models used to account for this type of spatial dependence, the spatial autoregressive (SAR) and the spatial error model (SEM). The SAR consists of a spatial lag of the dependent variable, whereas the SEM specification corrects for spatial correlation in the disturbance term. I follow Lacombe (2004b) to decide which model is most appropriate. The SAR and SEM model specification were each run and the SAR model captures more spatial dependence and consequently is used. The SAR model incorporates a spatial lag of the dependent variable to correct for this as follows:

$$v = \rho(Wv) + \beta\chi + \varepsilon \tag{3.2}$$

where  $\varepsilon$

$$\varepsilon \sim N(0, \sigma^2 I_n) \tag{3.3}$$

and the weighted matrix,  $W$ , is comprised of an  $n \times n$  matrix with zeros in the diagonal and off diagonal components are the weights by which the spatial dependence is characterized.<sup>3</sup> The matrix is multiplied by a set of neighbor characteristics for  $N$  number of nearest neighbors in terms of X-Y coordinates to produce the average neighbor characteristics described as  $\chi_2$  where  $\chi_2$  is a subset of  $\chi_1$ . The effect of the spatial lag,  $\rho$ , captures the spatial dependence of the house prices. This is similar to the spatial Durbin model, which includes a spatial lag of the dependent and all independent variables. Including all independent variables

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<sup>3</sup>A detailed explanation of the model can be found in Anselin (1988).

brings issues of multicollinearity, so only a subset of variables are included. The model then resembles a modified spatial Durbin and spatial autoregressive model as follows:

$$v = \rho(Wv) + \beta\chi_1 + \delta W\chi_2 + \varepsilon \quad (3.4)$$

where  $Wv$  is the weighted house price of  $N$  nearest neighbors and  $W\chi_2$  is the weighted neighbor characteristics. Now, all observations are defined as simultaneously dependent while also controlling for the effect of specific neighbor housing characteristics which influence own price. While this allows us to examine the influence of nearest neighbor house size on predicted house price, we must also incorporate the additional reference groups of surrounding neighbors, highest consuming (largest houses) neighbors and lowest consuming (smallest houses) neighbors respectively.

Following the Bayesian model comparison method described in Lesage and Pace (2009a), the optimal number of nearest neighbors is the number for which the model specification has the highest probability of describing the data. The model selection probabilities for nearest neighbors is less than 1% for all nearest neighbor specifications except seven, which has a probability greater than 99%. However, literature acknowledges that choosing the nearest number of neighbors is fairly arbitrary, typically ranging from 5-20 (Sedgley et al., 2008). Using seven as a starting point, the model was run for various combinations of nearest neighbors and further neighbors (who represent surrounding neighborhoods approximately within the district). The results from the full specification for various assumed neighbor definitions can be found in tables 3.1, 3.2, 3.3, 3.4, 3.5, 3.6, 3.7, 3.8, 3.9, respectively. A summary of results of the different model specifications with respect to the variables of interest can be found in Table 3.10.

Specifications for nearest neighbors less than six (with the exception of four, which produced results consistent with the final specification) resulted in insignificant results regarding the effect of nearest neighbor and further neighbors on predicted house price, suggesting that the two variables were not statistically different from one another. Specifications for nearest neighbors of six, seven, eight and nine and further neighbors of twelve, fourteen, sixteen, eighteen respectively yielded consistent results. The results weakened for further neighbors greater than eighteen, suggesting that those neighbors are too far away to significantly impact the predicted price. The final determination of eight nearest neighbors and sixteen further neighbors was chosen arbitrarily, although, as shown, minor variations of the optimal number support the results, which are discussed later in depth. On average, the nearest eight neighbors lie within .25 miles of any given house and the nearest sixteen neighbors lie within approximately .5 to .6 miles. These distances support the interpretation of within neighborhood and within district (or, surrounding neighborhoods) comparison.

The variable representing the largest houses in the district was calculated by averaging the house size of the top 5% of the largest houses in each of the nine districts in Columbus. Similarly, the variable representing the smallest houses was constructed by averaging the house size of the bottom 5% of the smallest houses in the district. The model specification varied to include the reference groups individually, with nearest neighbors being present in all three, since it has been shown to have an influence on predicted change in housing price. The model with all reference groups included can now be described as follows:

$$v = \rho(Wv) + \beta\chi + \delta W\chi_2 + \alpha_1 W_2 HouseSize + \alpha_2 Largest + \alpha_3 Smallest + \varepsilon \quad (3.5)$$

where  $W$  is the weighted matrix for the eight nearest neighbors,  $W_2$  is the weighted matrix for the ninth through sixteenth neighbors,  $\rho$  captures spatial dependence and  $\varepsilon \sim N(0, \sigma^2 I_n)$ . An increase in absolute consumption of housing is associated with a predicted change in house

Table 3.1: Spatial Autoregressive Model: Two as Nearest Neighbors, Four as Further Neighbors

Dependent Variable: Ln House Price

Variable	Columbus
Own House Size	0.355*** (0.011)
Further Neighbors'-House Size	0.022*** (0.005)
Nearest Neighbors'-House Size	0.001 (0.001)
$\rho$	0.289*** (0.011)
Proficiency	-0.018*** (0.001)
Onestory	0.043*** (0.005)
Airconditioning	0.108*** (0.005)
Fireplace	0.052*** (0.004)
FullBath	0.087*** (0.005)
PartBath	0.053*** (0.005)
Age	-0.492*** (0.029)
Age Squared	0.267*** (0.019)
Housesize Squared	-0.024*** (0.001)
Log Yardsize	0.111*** (0.005)
Deck	0.038** (0.017)
Tax Rate	0.066*** (0.003)
Racial Fract	-0.300*** (0.026)
Income	0.000*** (0.000)
Crime	0.001** (0.000)
R-Squared	0.7528

Table 3.2: Spatial Autoregressive Model: Three as Nearest Neighbors, Six as Further Neighbors

Dependent Variable: Ln House Price	
Variable	Columbus
Own House Size	0.352*** (0.011)
Further Neighbors'-House Size	0.018*** (0.005)
Nearest Neighbors'-House Size	-0.002 (0.001)
$\rho$	0.336*** (0.011)
Proficiency	-0.019*** (0.001)
Onestory	0.043*** (0.005)
Airconditioning	0.102*** (0.005)
Fireplace	0.051*** (0.004)
FullBath	0.083*** (0.005)
PartBath	0.051*** (0.005)
Age	-0.464*** (0.029)
Age Squared	0.236*** (0.019)
Housesize Squared	-0.023*** (0.001)
Log Yardsize	0.120*** (0.005)
Deck	0.044** (0.017)
Tax Rate	0.073*** (0.003)
Racial Fract	-0.290*** (0.026)
Income	0.000*** (0.000)
Crime	0.001** (0.000)
R-Squared	0.7526



Table 3.3: Spatial Autoregressive Model: Four as Nearest Neighbors, Eight as Further Neighbors

Dependent Variable: Ln House Price

Variable	Columbus
Own House Size	0.353*** (0.011)
Further Neighbors'-House Size	0.018*** (0.005)
Nearest Neighbors'-House Size	-0.019*** (0.001)
$\rho$	0.374*** (0.011)
Proficiency	-0.020*** (0.001)
Onestory	0.043*** (0.005)
Airconditioning	0.099*** (0.005)
Fireplace	0.050*** (0.004)
FullBath	0.083*** (0.005)
PartBath	0.051*** (0.005)
Age	-0.464*** (0.029)
Age Squared	0.222*** (0.019)
Housesize Squared	-0.023*** (0.001)
Log Yardsize	0.127*** (0.005)
Deck	0.044** (0.017)
Tax Rate	0.078*** (0.003)
Racial Fract	-0.268*** (0.026)
Income	0.000*** (0.000)
Crime	0.001** (0.000)
R-Squared	0.7518

Table 3.4: Spatial Autoregressive Model: Five as Nearest Neighbors, Ten as Further Neighbors

Dependent Variable: Ln House Price

Variable	Columbus
Own House Size	0.358*** (0.011)
Further Neighbors'-House Size	0.016** (0.005)
Nearest Neighbors'-House Size	-0.017 (0.001)
$\rho$	0.384*** (0.011)
Proficiency	-0.019*** (0.001)
Onestory	0.046*** (0.005)
Airconditioning	0.097*** (0.005)
Fireplace	0.050*** (0.004)
FullBath	0.083*** (0.005)
PartBath	0.051*** (0.005)
Age	-0.452*** (0.029)
Age Squared	0.209*** (0.019)
Housesize Squared	-0.023*** (0.001)
Log Yardsize	0.134*** (0.005)
Deck	0.053** (0.017)
Tax Rate	0.075*** (0.003)
Racial Fract	-0.256*** (0.026)
Income	0.000*** (0.000)
Crime	0.001** (0.000)
R-Squared	0.7504

Table 3.5: Spatial Autoregressive Model: Six as Nearest Neighbors, Twelve as Further Neighbors

Dependent Variable: Ln House Price	
Variable	Columbus
Own House Size	0.359*** (0.011)
Further Neighbors'-House Size	0.014** (0.005)
Nearest Neighbors'-House Size	-0.016** (0.001)
$\rho$	0.396*** (0.011)
Proficiency	-0.018*** (0.001)
Onestory	0.047*** (0.005)
Airconditioning	0.096*** (0.005)
Fireplace	0.050*** (0.004)
FullBath	0.082*** (0.005)
PartBath	0.051*** (0.005)
Age	-0.453*** (0.029)
Age Squared	0.204*** (0.019)
Housesize Squared	-0.024*** (0.001)
Log Yardsize	0.139*** (0.005)
Deck	0.058** (0.017)
Tax Rate	0.073*** (0.003)
Racial Fract	-0.251*** (0.026)
Income	0.000*** (0.000)
Crime	0.001** (0.000)
R-Squared	0.7491

Table 3.6: Spatial Autoregressive Model: Seven as Nearest Neighbors, Fourteen as Further Neighbors

Dependent Variable: Ln House Price

Variable	Columbus
Own House Size	0.363*** (0.011)
Further Neighbors'-House Size	0.013** (0.005)
Nearest Neighbors'-House Size	-0.020*** (0.001)
$\rho$	0.412*** (0.011)
Proficiency	-0.019*** (0.001)
Onestory	0.047*** (0.005)
Airconditioning	0.093*** (0.005)
Fireplace	0.049*** (0.004)
FullBath	0.081*** (0.005)
PartBath	0.051*** (0.005)
Age	-0.452*** (0.029)
Age Squared	0.197*** (0.019)
Housesize Squared	-0.024*** (0.001)
Log Yardsize	0.141*** (0.005)
Deck	0.061** (0.017)
Tax Rate	0.075*** (0.003)
Racial Fract	-0.246*** (0.026)
Income	0.000*** (0.000)
Crime	0.001** (0.000)
R-Squared	0.7477

Table 3.7: Spatial Autoregressive Model: Eight as Nearest Neighbors, Sixteen as Further Neighbors

Dependent Variable: Ln House Price

Variable	Columbus
Own House Size	0.366*** (0.000)
Surrounding Neighbors'-House Size	0.011*** (0.040)
Nearest Neighbors'-House Size	-0.017*** (0.032)
$\rho_1$	0.416*** (0.000)
Proficiency	-0.018*** (0.000)
Onestory	0.049*** (0.000)
Airconditioning	0.091*** (0.000)
Fireplace	0.050*** (0.000)
FullBath	0.081*** (0.000)
PartBath	0.051*** (0.000)
Age	-0.450*** (0.000)
Age Squared	0.194*** (0.000)
Housesize Squared	-0.024*** (0.000)
Log Yardsize	0.143*** (0.000)
Deck	0.063*** (0.000)
Tax Rate	0.072*** (0.000)
Racial Fract	-0.244*** (0.000)
Income	0.001*** (0.000)
Crime	0.001** (0.041)
R-Squared	0.7469

Table 3.8: Spatial Autoregressive Model: Nine as Nearest Neighbors, Eighteen as Further Neighbors

Dependent Variable: Ln House Price

Variable	Columbus
Own House Size	0.367*** (0.011)
Further Neighbors'-House Size	0.010* (0.005)
Nearest Neighbors'-House Size	-0.016** (0.001)
$\rho$	0.415*** (0.011)
Proficiency	-0.017*** (0.001)
Onestory	0.050*** (0.005)
Airconditioning	0.092*** (0.005)
Fireplace	0.050*** (0.004)
FullBath	0.082*** (0.005)
PartBath	0.052*** (0.005)
Age	-0.455*** (0.029)
Age Squared	0.196*** (0.019)
Housesize Squared	-0.024*** (0.001)
Log Yardsize	0.145*** (0.005)
Deck	0.065** (0.017)
Tax Rate	0.069*** (0.003)
Racial Fract	-0.246*** (0.026)
Income	0.000*** (0.000)
Crime	0.001** (0.000)
R-Squared	0.7465

Table 3.9: Spatial Autoregressive Model: Ten as Nearest Neighbors, Twenty as Further Neighbors

Dependent Variable: Ln House Price

Variable	Columbus
Own House Size	0.370*** (0.011)
Further Neighbors'-House Size	0.001 (0.005)
Nearest Neighbors'-House Size	-0.007 (0.001)
$\rho$	0.415*** (0.011)
Proficiency	-0.017*** (0.001)
Onestory	0.050*** (0.005)
Airconditioning	0.092*** (0.005)
Fireplace	0.050*** (0.004)
FullBath	0.082*** (0.005)
PartBath	0.052*** (0.005)
Age	-0.460*** (0.029)
Age Squared	0.195*** (0.019)
Housesize Squared	-0.025*** (0.001)
Log Yardsize	0.147*** (0.005)
Deck	0.068** (0.017)
Tax Rate	0.067*** (0.003)
Racial Fract	-0.245*** (0.026)
Income	0.000*** (0.000)
Crime	0.001** (0.000)
R-Squared	0.7461

Table 3.10: Spatial Autoregressive Model: Summary of Results for Different Number of Neighbors

Nearest, Further	Own House	Nearest Neighbor	Further Neighbor	Spatial Dependence
Two, Four	0.355***	0.001	0.022***	0.289***
Three, Six	0.352***	-0.002	-0.118***	0.336***
Four, Eight	0.353***	-0.019***	0.018***	0.374***
Five, Ten	0.358***	-0.017	0.014**	0.384***
Six, Twelve	0.359***	-0.016**	0.013**	0.396***
Seven, Fourteen	0.363***	-0.020***	0.270***	0.412***
Eight, Sixteen	0.366***	-0.017***	0.011***	0.416***
Nine, Eighteen	0.367***	-0.016**	0.010*	0.415***
Ten, Twenty	0.370***	-0.007***	0.001	0.415***

Note: Z-probabilities are indicated as \*\*\* at 1%, \*\* at 5%, and \* at 10%.

price by  $\beta_{HouseSize}$ . The influence of an increase in nearest neighbor housing consumption is described by  $\delta_{HouseSize}$ , further neighbors by  $\alpha_1$ , largest houses by  $\alpha_2$  smallest houses by  $\alpha_3$ . The model is run for surrounding neighborhoods, the largest houses in the district and the smallest houses in the district separately. A negative coefficient implies an envy effect is present. An increase in house size of that particular reference group is associated with a negative predicted change in house price. A positive coefficient implies a reflected glory effect, where predicted house price increases when house size of a reference group increases.

## 4 Results and Discussion

Three model specifications were run, one with the further neighbors, another with the poorest neighbors and the third with the richest neighbors (all specifications included nearest neighbors and otherwise identical model specification). Detailed results for all specifications are reported in Table 3.11, Table 3.12 and Table 3.13 respectfully. A summary of results of the variables of interest are reported in Table 3.14.

The physical housing characteristics behave as expected. The presence of air conditioning,



Table 3.11: Spatial Autoregressive Model: Further Neighbors as Reference Group

**Spatial Autoregressive Model: Further Neighbors**

Dependent Variable: Ln House Price

Variable	Coefficient	T-statistic
Own House Size	0.366***	32.3
Further Neighbors-House Size Increase	0.011***	2.1
Nearest Neighbors-House Size Increase	-0.017***	-2.1
$\rho$	0.415***	61.2
Proficiency	-0.018***	-21.4
Onestory	0.049***	9.4
Airconditioning	0.092***	18.3
Fireplace	0.050***	12.4
FullBath	0.082***	16.0
PartBath	0.051***	10.2
Age	-0.451***	-15.7
Age Squared	0.195***	10.5
Housesize Squared	-0.024***	-13.9
Log Yardsize	0.143***	29.4
Deck	0.062***	3.7
Tax Rate	0.072***	35.9
Pollution	0.000	-1.2
Racial Fract	-0.245***	-9.2
Income	0.000***	136.8
Crime	0.001**	2.0
Nearest Neighbors-Proficiency	0.020***	23.6
Nearest Neighbors-Age	0.197***	11.5
Nearest Neighbors-Log Yardsize	-0.235***	-32.9
Nearest Neighbors-Tax Rate	-0.073***	-35.5
Nearest Neighbors-Crime	0.000**	-3.5
Intercept	6.895***	91.0
R-Squared	0.7466	.

Note: Z-Probabilities are indicated as \*\*\* at 1%, \*\* at 5%, and \* at 10%.

Table 3.12: Spatial Autoregressive Model: Smallest Houses as Reference Group

Dependent Variable: Ln House Price

Variable	Coefficient	T-statistic
House Size	0.367***	32.4
Smallest Neighbors House Size Increase	0.038**	2.9
Nearest Neighbor House Size Increase	-0.007***	-2.1
$\rho$	0.410***	60.6
Proficiency	-0.018***	-21.0
Onestory	0.050***	9.5
Airconditioning	0.091***	18.1
Fireplace	0.050***	12.6
FullBath	0.082***	16.1
PartBath	0.052***	10.3
Age	-0.448***	-15.6
AgeSquared	0.193***	10.4
Housesize Squared	-0.024***	-13.9
Log Yardsize	0.142***	29.3
Deck	0.061***	3.6
Tax Rate	0.071***	35.2
Pollution	0.000	-1.3
Racial Fract	-0.233***	-9.20
Income	0.000***	139.0
Crime	0.001**	2.0
Nearest Neighbors-Proficiency	0.020***	23.3
Nearest Neighbors-Age	0.186***	11.7
Nearest Neighbors-Ln Yard size	-0.201***	-32.7
Nearest Neighbors-Tax rate	-0.072***	-35.0
Nearest Neighbors-Crime	-0.001***	-3.4
Intercept	6.924***	91.5
R-Squared	0.7474	.

Note: Z-probabilities are indicated as \*\*\* at 1%, \*\* at 5%, and \* at 10%.

Table 3.13: Spatial Autoregressive Model: Largest Houses as Reference Group

Dependent Variable: Ln House Price

Variable	Coefficient	T-statistic
House Size	0.364***	32.3
Largest Neighbors House Size Increase	-0.012**	-8.1
Nearest Neighbor House Size Increase	-0.014***	-2.0
$\rho$	0.410***	60.6
Proficiency	-0.017***	-20.4
Onestory	0.047***	8.9
Airconditioning	0.094***	18.6
Fireplace	0.048***	11.9
FullBath	0.081***	15.9
PartBath	0.051***	10.2
Age	-0.495***	-17.04
AgeSquared	0.227***	12.0
Housesize Squared	-0.024***	-14.0
Log Yardsize	0.144***	29.8
Deck	0.056***	3.3
Tax Rate	0.070***	34.7
Pollution	0.000	-1.2
Racial Fract	-0.272***	-10.7
Income	0.000***	144.7
Crime	0.001**	2.1
Nearest Neighbors-Proficiency	0.020***	23.0
Nearest Neighbors-Age	0.185***	10.8
Nearest Neighbors-Ln Yard size	-0.235***	-33.0
Nearest Neighbors-Tax rate	-0.071***	-34.6
Nearest Neighbors-Crime	-0.001***	-3.4
Intercept	7.001***	91.7
R-Squared	0.7498	.

Note: Z-probabilities are indicated as \*\*\* at 1%, \*\* at 5%, and \* at 10%.

Table 3.14: Summary of Results: The Effect of an Increase in Housing Consumption of Various Reference Groups on Predicted House Price

Dependent Variable: Ln House Price

Variable	Further	T-Stat	Smallest	T-Stat	Largest	T-Stat
Own House Size	0.366***	32.3	0.367***	32.4	0.364***	32.3
ReferenceGroup House Size	0.011***	2.1	0.038**	2.9	-0.012**	-8.1
Nearest Neighbor House Size	-0.017***	-2.1	-0.007***	-2.1	-0.014***	-2.0
$\rho$	0.415***	61.2	0.410***	60.6	0.410***	60.6
R-Squared	0.7466	.	0.7474	.	0.7498	.

Note: Z-probabilities are indicated as \*\*\* at 1%, \*\* at 5%, and \* at 10%.

a fireplace, a deck and more bathrooms have a positive and significant effect. The size of the house and the yard have a positive effect and the age of the house has a negative effect. House size squared has a negative effect due to diminishing returns and age squared is positive and significant, suggesting historical value for much older homes. The effect of racial fractionalization is negative, significant and very large as expected. Income, crime and pollution have a negligible effect and proficiency exams report a negative, but extremely small effect.

The influence of a change in the housing consumption of the different reference groups differed significantly. Regarding nearest neighbors, the associated effect of an increase in the housing consumption on predicted house price is negative. The average effect of an increase in the average house size of the nearest neighbors on predicted house price for the three model specifications is  $-(0.0126)$  and is associated with a marginal willingness to pay of  $-\$313.81$  to increase the size of average nearest neighbor house by 100sqft from the mean.<sup>4</sup> This implies individuals value a decrease in the housing consumption of their nearest neighbor, keeping absolute house size constant, suggesting that individuals do exhibit envy to some degree

<sup>4</sup>Willingness to pay calculated by  $\beta_x(\frac{1}{1-\rho})\bar{y}$ , following (Kim et al., 2003a). Because the house size is given in thousands of square feet, the WTP is multiplied by (0.1) to see the effect of a change in 100 square feet instead of 1000 square feet.

with respect to this reference group. All other things equal, an increase in the size of the nearest neighbors' house will decrease the predicted house price.<sup>5</sup>

However, the associated effect of a change in housing consumption of further neighbors was quite different, (0.011). An increase of average further neighbor house size by 100sqft from the mean is associated with a marginal willingness to pay \$272.55, which suggests that individuals may be basking in the reflected glory of the reference group consumption. A similar tendency was found with respect to a change in relative housing consumption of the smallest houses in the district, (0.038). An increase in the smallest houses in the district by 100ft from the mean is associated with a marginal willingness to pay of \$941.53. Conversely, the associated effect of an increase in housing consumption by the largest houses in the neighborhood is -(0.012), with a marginal willingness to pay of -\$297.33, supporting the hypothesis that individuals “compare up”. Taken together, it appears individuals envy their nearest neighbors and the rich, while basking in the reflected glory of their further neighbors and the poor. This is not to say that individuals do not envy the surrounding neighbors and the poor or bask in the reflected glory of the nearest neighbors and the rich, simply that one effect appears to be dominating the other. The effect of an increase in absolute house size on predicted house price is significantly larger (0.366) than all associated effects of an equivalent change in relative house size and is associated with a marginal willingness to pay of \$9060.15. The marginal willingness to pay for absolute and relative house size can be found in Table 3.15.

The propensity to envy nearest neighbors and not further neighbors may be because individuals generally want to be associated with higher consuming individuals, but do not want to confront the disparity directly. Concerning immediate neighbors with whom individuals interact daily, individuals prefer to maintain relative status, but further neighbors with whom they do not experience as much direct interaction (but are perhaps associated

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<sup>5</sup>This result is in direct contrast to previous findings by Turnbull et al. (2006), which suggests that the relationship may not hold for all housing markets. Further research is needed to test these and previous findings.

Table 3.15: Willingness To Pay (WTP) for an Increase in Housing Consumption of Various Reference Groups

Marginal implicit prices		
Reference Group	Willingness to Pay for an Increase in Reference Group House Size	Percent of housing price
Nearest Neighbors	-\$313.84	0.215%
Further Neighbors	\$272.55	0.187%
Smallest Houses in District	\$941.53	0.646%
Largest Houses in District	-\$297.33	0.204%
Own House	\$9,060.15	6.219%

Note: WTP calculated by  $\beta_x (\frac{1}{1-\rho}) \bar{y}$ . Calculations based on an increase of 100sqft from the mean for own house and neighbors' house, separately (the estimates were multiplied by (0.1) because the house size variable is measured in thousands of square feet). The average of the three coefficients obtained for the different model specifications were used for own house and nearest neighbor house increases.

with) individuals prefer an increase in their consumption. It appears there is value to being associated with the part of town that has larger houses than own house (for reasons apart from the amenities and positive externalities), but also a value to having a house bigger than an individual's immediate neighbors.

The result that individuals envy the rich, or highest consuming individuals, is not surprising. Living in an area where the largest houses are much larger than one's house does appear to negatively affect predicted house price, probably because the house feels less valuable relative to if the house was in an area with a smaller size disparity with respect to the largest houses. With regards to the influence of poorest, or lowest consuming individuals, the concept of basking in the reflected glory has a slightly different interpretation. Rather than valuing an increase in consumption because of a positive association, perhaps an increase in consumption of this reference group reduces negative association. Having extremely low housing consumption levels within a district may have a negative connotation attached to it, so any increase in consumption is of value to other houses associated with the area. It may also be that individuals exhibit empathy towards this reference group and consequently do not value a decline in their housing consumption.

## 5 Conclusion

This paper examines whether the envy effect or the reflected glory effect of housing consumption dominates with respect to different reference groups. I examine the change in predicted house price associated with a change in average house size of nearest neighbors, further neighbors, largest houses in the district, and the smallest houses within the district. If the envy effect dominates, predicted house price associated with an increase in average reference group house size would decrease. This envy effect relates to the conspicuous consumption effect coined by Veblen (1899). If instead, individuals value being associated with higher consumption levels, the predicted house price associated with an increase in average

reference group house size would increase. In this sense, individuals are ‘basking in the reflected glory’ of others’ consumption (Cialdini et al., 1976). While they may presumably prefer to increase their own consumption, they still value an increase in the consumption of those with whom they may be associated.

Results imply that individuals prefer to have a house larger than their nearest neighbor and live in a district with a smaller difference between own house size and that of the largest houses in the district. This suggests individuals display evidence of the envy effect (or, similarly, they derive value from having a relatively larger home) with respect to these reference groups. This result lies in contrast with the findings of Turnbull et al. (2006), which observed that relatively small houses sell at a premium. The use of spatial autoregressive models and a much larger data set in this paper allows for a broader range of theoretical outcomes than previous analysis. The disaggregation of neighbor groups likely explains the different findings.

Concerning more distant neighbors and the smallest houses in the district, the opposite influence is observed. An increase in average house size of these reference groups is associated with a positive change in predicted own house price. Regarding more distant neighbors, this suggests that the reflected glory effect dominates the envy effect. Individuals value being associated with high levels of consumption by this reference group. With respect to the smallest houses, there are two possible explanations. It may be that decreased housing consumption of the smallest houses brings a negative connotation to the area that is stronger than any benefit of having a relatively larger house. Alternatively it may be that individuals are exhibiting empathy towards this reference group and do not gain from a decrease in the consumption levels of the relatively poor (or both explanations may contribute).

Taken together, individuals are primarily comparing themselves to their nearest neighbor and the highest consuming in the district and primarily have an association relationship with further neighbors (neighbors surrounding own neighborhood) and the lowest consuming in the district. This does not imply that individuals do not compare themselves to further



neighbors and the lowest consuming or do not gain value through association with the highest consuming neighbors and nearest neighbors, but rather, the reflected glory or envy effect dominates the other. Additionally, the relationship between own house size and price is of greater magnitude than all of the relationships between reference group house size and own house price *combined*.

If housing can be thought of as a status good, this implies the importance of relative consumption changes with respect to different reference groups. Housing consumption is one of numerous goods that are thought to be status goods and it would be useful to examine whether other status goods follow similar consumption tendencies. Regarding the housing market in particular, advances in spatial autocorrelation techniques allow us to isolate particular variables whose effect previously have been hard to separate from unobservable latent variables that exist in the housing market. As such, these methods are useful in extracting implicit prices for many other interesting goods, as well as revisiting earlier findings. While this chapter and its predecessor concentrated on the relationship between neighbor house size and house price around the mean, the next chapter will relax the assumption of a representative consumer.

# Chapter 4

## Who Cares About the Joneses? A Spatial Quantile Approach to Relative House Size Preference

### 1 Introduction

A century ago, coveting thy neighbors assets was condemned by society as a mortal sin. With the advent of mass production and the resulting spread of a wider consumer economy at the turn of the twentieth century, many individuals could afford goods once offered to only the super wealthy. Exposure to these goods through an expanding media influence is thought to have led to an economy where individuals place a large importance to "keeping up with the Joneses", where individuals consume goods to indicate social status. In particular, the importance of establishing relative status appears to be a strong motivation for consumption of these goods. Although the desire for relative status has been acknowledged by every economist since Adam Smith, it has been argued that relative status has become increasingly important in more recent years (Frank, 1985). It then becomes a relevant question to consider who exactly, cares the most about relative status? Is it the poor who are surrounded by

those wealthier than them? The middle class who are within reach of the wealthy through reality television and knock-off goods? The wealthy who are maintaining their status as top consumers?

Popular media often portrays the middle class as the consumers obsessed with appearing wealthy. It has even been proposed that the rise in shoplifting of luxury food during the last recession is victim to “middle-class soccer moms” who are stealing for their own consumption in a desire to appear wealthy rather than the more typical low income thieves (Fresco, 2009). The desire for high status goods is often used as a partial explanation for the inability of the working-poor in the United States to rise out of poverty. On the other end of the spectrum, the wealthiest are chastised for spending money on goods that serve no other purpose than to signal status, denouncing the consumption as unnecessary (Frank, 2008).

Consumption patterns of status goods can provide evidence of this behavior if it does exist. Housing size is thought to be one such status good and lends itself well to quantitative analysis. This chapter examines how the willingness to pay of individuals for a decrease in the house size of their nearest neighbor, controlling for spatial dependence, varies across the distribution of housing prices. I employ a two-stage quantile regression approach from Amemiya (1982) with the spatial instrument approach of Kelejian and Prucha (1988). Using the Brasington Ohio dataset, the associated effect of a change in the neighbors’ house size on housing price at different quantiles of the distribution are compared. There is no evidence that a representative agent is appropriate when discussing relative status importance (to the contrary, there is reason to believe that individuals may systematically differ in this respect) and this methodology highlights important differences in preferences for status.

The remainder of the chapter is organized as follows. Section 2 discusses the literature of house size and relative status, hedonic price theory and quantile regression. The model specification and data are described in section 3. Section 4 describes the results and section 5 concludes.

## 2 Literature Review

### 2.1 Relative Status

Although casually mentioned by economists for the last two centuries, and later developed by Duesenberry (1949) and Pollak (1976), only recently has the desire for relative status or wealth been subject to empirical scrutiny. An emerging “happiness” literature addresses the desire for status primarily through stated preference survey data. However, there are significant problems with stated preference surveys stemming from interviewer bias, bias from ordering of questions, inability of individuals to predict future happiness, a desire to give the socially correct answer, and distortion from stating preferences without cost among other things (Bertrand and Mullainathan, 2001). To avoid these problems, a revealed preference approach of the housing market is employed. With respect to status, questions are typically some version of “Would you rather live in a world where you had a lot of wealth, but those around you had even more or a world where you had less, but more than those around you?” coupled with, “On a scale of 1-7 how happy are you?” and the effect of self reported happiness on changes in relative income is examined. The results of these studies suggest the effect of relative wealth on stated utility is large, sometimes even larger than the effect of absolute wealth (Solnick and Hemenway, 1998), (Johansson-Stenman et al., 2002), (Alesina et al., 2003), (Carlsson et al., 2007), (Carbonell, 2005), (Luttmer, 2005) and (Alpizar et al., 2005). To date, the literature has not addressed the question of the importance of relative status across income groups.

In addition to addressing the question of importance across the distribution, this study acts as a revealed preference test of the validity of survey data conclusions. There are strong reasons to question stated preferences as a substitute for revealed preferences. As mentioned previously, survey responses are influenced by many factors not related to the question such as interviewer characteristics, ordering of questions, and a desire to give a “socially acceptable” answer to name a few (Benney et al., 1956; Hyman et al., 1954; Jaeger and Pennock, 1961;

Edwards, 1957). In addition to these shortfalls lies a few more significant problems with survey data. The first is that even if individuals had an incentive to be truthful (which itself is a broad assumption given there is no cost to misrepresenting preferences), it may be impossible to accurately predict changes in happiness caused by hypothetical future scenarios (Gilbert, 2007). That is, even if individuals are truthfully reporting their predicted changes in utility, their predictions may not be accurate. The second problem is that if individuals were truthful and could accurately predict hypothetical changes in happiness, it doesn't hold that interpersonal comparisons of happiness can be made (Varian, 2003). If interpersonal comparisons are not allowed, then conclusions from aggregated survey responses are not valid except as individual case studies.

However, revealed preference approaches are also not without shortcomings. Price, or willingness to pay, may not capture utility generated by the consumer. Frank (1985) describes two possible reasons for this discrepancy. The first is that individuals may not always be rational decision makers and consequently make systematic errors in judgement, evidenced by the feeling of buyers remorse. A second possible reason is perhaps individuals cannot efficiently process information, leading to decisions that are not utility-maximizing. Additionally, revealed preference approaches are limited to goods for which there is a traditional market. The use of stated preference survey data has been justified on the grounds that these types of goods may be significant determinants of utility. However, it is useful, if possible, to see if the survey data conclusions are consistent with revealed preference data conclusions. In addition to the the main interest of this study, these results attempt to provide such a contribution.

## **2.2 Hedonic Price Theory**

Formal hedonic markets, first developed by Rosen (1974), assume housing as a bundle of goods. Each of the goods, whether observed or unobserved, has an implicit price. The implicit price, or willingness to pay, can be derived for each good, given a large enough

sample. The willingness to pay is generally reported for the goods at the mean house price within a given sample.

Complicating the analysis, hedonic price models must account for the spatial dependence of the dependent variable, housing price. When a change in a housing characteristic has an effect on the housing price, that housing price will affect the housing price of nearby homes. Two models typical account for spatial spillovers, the spatial autoregressive model (SAR), which incorporates a spatial lag of the dependent variable, and the spatial error model (SEM), which corrects for spatial correlation in the error term. All previous literature using the Brasington dataset supports the use of the SAR model and diagnostic tests concur. As such, I limit the discussion to the SAR model. For a detailed explanation of both models, please see Anselin (1988).

The standard hedonic price model is described as

$$\nu = X\beta + \varepsilon, \tag{4.1}$$

where  $\nu$  is an  $n \times 1$  vector representing the housing price,  $X$  is the  $n \times m$  vector of  $m$  explanatory characteristics of the observation and  $\varepsilon$  is normally distributed with constant variance and zero mean. The SAR model incorporates the spatial lag as follows

$$\nu = \rho(W\nu) + X\beta + \varepsilon. \tag{4.2}$$

Equation (4.2) includes the dependent variable on the right-hand side of the equation, lagged by the  $n \times n$  spatial weight matrix  $W$ .<sup>1</sup> Since the Brasington dataset includes the latitude-longitudinal coordinates of the individual houses, the weight matrix is based on the  $N$  “nearest neighbors,” where  $N$  is determined to be seven, supported by model selection tests<sup>2</sup>.

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<sup>1</sup>Adding a spatial lag does add a problem of potential endogeneity (Anselin, 1988). Given the nature of the data (there is only information on the houses sold) a two-stage Heckman procedure is not applicable. The literature notes such problems arising from this issue.

<sup>2</sup>I apply Bayes’ Rule to model selection to determine the model specification (the nearest number of neighbors) that has the highest probability of being the true model, given the data and the probability of

A discussion and results of optimal number of neighbors analysis can be found in Chapter 2. The optimal number of nearest neighbors is found to be six, and the average distance to the sixth neighbor is approximately .25 miles.

Hedonic analysis has been employed to derive an implicit price for housing characteristics such as bedrooms and bathrooms, as well as neighborhood or location characteristics such as school quality (Brasington and Hite, 2003), air pollution (Smith and Deyak, 1975), (Kiel and McClain, 1995), (Chattopadhyay, 1999), (Beron and J. Murdoch, 2001), (Kim et al., 2003a) and water pollution (Hoehn et al., 1987), hazardous waste sites (Kohlhase, 1991), (Nelson et al., 1992), (Hite et al., 2001), and environmental quality (Brasington and Hite, 2003). The majority of recent hedonic analysis have incorporated a spatial dependence component and have found it to be significant (Brasington and Hite, 2003).

## 2.3 Quantile Regression

If all consumers are identical, the willingness to pay for a particular variable is consistent for all housing prices in the sample. However, housing characteristics may not be valued the same across the entire distribution (Newsome and Zietz, 2002). It is quite reasonable to expect that consumers of low-price homes may value a third bathroom, for example, differently than a consumer of a high-priced home. Even if homeowners only differ with respect to their income constraint, we would still expect the demand for some housing characteristics to differ across social groups, according to their respective norms (Durlauf, 2001). This divergence violates the representative agent assumption made when discussing the marginal effect of the independent variables for the mean dependent variable.<sup>3</sup> Given the limitations of the representative agent assumption, a quantile regression is appropriate for hedonic price models (Zietz et al., 2008).

Quantile regression estimates the conditional quantile, or percentage, to observe the effect of a change in the independent variables at different data points other than the mean

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nearest neighbors being seven is over 99%.

<sup>3</sup>For an in-depth critique of the representative agent, see Kirman (1992)

(Koenker, 1978). For example, it may be that the effect of a third bathroom on housing price for the 95<sup>th</sup> percentile of the housing price distribution is some  $\beta^{.95}$  that is significantly different than the effect of a third bathroom on housing price for the 5<sup>th</sup> of the housing distribution,  $\beta^{.05}$ . That is, houses whose price are around the top 95<sup>th</sup> percentile of the overall sample may change more in response to an additional bathroom than houses around the bottom 5<sup>th</sup> percentile of housing prices. This would suggest that consumers who purchase more expensive homes value the additional bathroom more than consumers of lower priced homes. In the same way, quantile regression allows us to observe which consumers value the relative size of their house the most.

Traditional OLS analysis provides the  $\beta$  estimate around the mean dependent variable. For a random sample  $\{y_1, \dots, y_n\}$ , the solution minimizes the sum of absolute deviations.

$$\min \sum |y_i - \xi| \tag{4.3}$$

Quantile regression analysis is concerned with  $\beta$  estimates at percentiles other than the median. The conditional mean is generated by minimizing the weighted sum of absolute deviations. Observations are weighted differently depending on whether they fall above or below the conditional quantile. Additionally, because observations around the quantile in question are weighted more heavily, quantile regressions are less sensitive to outliers. For the special case of the 50<sup>th</sup>, the weights are symmetrical. The general  $p^{\text{th}}$  sample quantile  $\xi(p)$  may be formulated as the solution of the optimization problem

$$\min \sum \rho_p |y_i - \xi| \tag{4.4}$$

where  $\rho_p(z) = z(p - I(z < 0))$ ,  $0 < p < 1$  and  $I$  is some indicator function. The linear conditional quantile function,  $Q(p|X = x) = x'\beta(p)$ , can be estimated by solving

$$\widehat{\beta}(p) = \operatorname{argmin}_{\beta \in \mathbf{R}^p} \sum \rho_p |y_i - x'_i \beta| \tag{4.5}$$



for any quantile  $p \in (0, 1)$ . It has been suggested that segmenting the data into different percentiles and minimizing the sum of the squared errors for each subset of data would allow for the same analysis. However, data truncation of this nature would create biased parameter estimates (Heckman, 1976; Zietz et al., 2008). Quantile regression avoids this type of sample selection bias because all data points are used in determining the beta estimate conditional on the quantile.

However, quantile regression analysis does not necessarily account for spatial dependence. It does not hold that housing prices around the same quantile will be spatially close as well. Only recently have researchers begun to incorporate spatial autocorrelation into quantile regression analysis (Su and Yang, 2007). This paper most closely follows Zietz et al. (2008), who incorporate a spatial lag variable and employ a two-stage instrumental variable procedure to estimate determinants of housing prices across quantiles.

This analysis combines the two-stage quantile regression approach from Amemiya (1982) with the spatial instrument approach of Kelejian and Prucha (1988) to estimate Equation (4.2) with quantile regression. First,  $W_y$  is regressed on  $[X:WX]$  using OLS (excluding the constant and dummy variables in  $WX$ ) to generate predicted values of  $\hat{W}y$ . Then, a quantile regression of  $y$  on  $[\hat{W}y:X]$  that is conditional on the percentile of choice is estimated. Finally, bootstrap standard errors are calculated by taking samples with replacement on the  $(y_i, x_i, \sum_j W_{ij}y_i, \sum_j W_{iu}x_i)$  set and repeat the first and second steps.<sup>4</sup>

### 3 Data and Model Specification

As with the previous chapters, this study uses the Brasington Ohio data set. A modified SAR model is employed. In addition to incorporating a spatial lag of the dependent variable, log of the house price, a spatial lag of some of the independent variables are included as well. In particular, the variable of interest is the size of the surrounding neighbor houses. Other

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<sup>4</sup>The samples used to calculate include  $\sum_j W_{ij}y_i$  and  $\sum_j W_{iu}x_i$  to ensure the spatial lag is based on actual neighbors in the original sample, not the bootstrap sample.

spatial lags were included if they did not show signs of multicollinearity. The general model is then

$$\nu = \rho(W\nu) + \beta_1(X_1) + \beta_2(WX_2) + \varepsilon, \quad (4.6)$$

where  $\nu$  is the log of the house price,  $\rho$  is the spatial coefficient,  $\beta_1$  the effect of the independent variables, and  $\beta_2$  is the effect of the nearest neighbors' house characteristics  $X_2$ , which are a subset of  $X_1$ , conditional on the quantile. Our variable of interest is the effect of an increase in the size of the nearest neighbors house on own house price,  $W\beta_{housesize}$ , conditional on the 10<sup>th</sup>, 25<sup>th</sup>, 50<sup>th</sup>, 75<sup>th</sup> and 90<sup>th</sup> percentile respectively.

If I find  $|\beta_{W-hsize}^{10}| < |\beta_{Whsize}^{25}| < |\beta_{Whsize}^5| < |\beta_{Whsize}^{75}| < |\beta_{Whsize}^{90}|$ , for example, then the consumers of houses in the lower quantiles (10<sup>th</sup>-25<sup>th</sup> percentile) are willing to pay less to decrease the size of their nearest neighbors house relative to consumers of the middle quantile (50<sup>th</sup> percentile), who are willing to pay less than the upper-quantile consumers (75<sup>th</sup>-90<sup>th</sup> percentile). This would imply that lower-quantile consumers care less about status than middle-quantile consumers and middle-quantile consumers care less about status than upper-quantile consumers. Alternatively, it may be that consumers care less about status as income rises, in which case we expect the reverse to be true. Another possibility is that it is the middle-quantile who care the most about “keeping up with the Joneses” and we would find  $|\beta_{Whsize}^5| > |\beta_{Whsize}^{75}|, |\beta_{Whsize}^{90}|$  and  $|\beta_{Whsize}^5| > |\beta_{Whsize}^{25}|, |\beta_{Whsize}^{10}|$ . For all cases, it is expected that a decrease in the size of the nearest neighbors' house will increase own house price. The question of interest is the difference in the magnitude of effect.

### 3.1 Variables

Housing price is influenced by the quality of the house and the quality of the neighborhood. Following the literature, housing quality is assumed to be a function of the number of bedrooms, bathrooms, age, yard size, house size, presence of air conditioning, deck or pool and fireplace. Neighborhood quality is influenced by school quality, tax rate, pollution, degree of

racial fractionalization and crime rate (Brasington and Hite, 2003). School quality is thought to be influenced by expenditure per pupil and test scores (Brasington, 1999). Therefore, school quality is measured by both the difference between the percentage of students passing the 9th grade proficiency exam and the average pass rate in the MSA and the expenditure per pupil by district.

The size of the house and yard, the addition of rooms, air conditioning, deck, and fireplace as well as increases in school quality should positively increase the house price. An increase in pollution, degree of racial fractionalization and crime rate ought to negatively influence house price. The effect of an increase in the tax rate is ambiguous; it may be negative if it represents a burden on households or positive if it is a proxy for public good provision. Similarly the effect of the age of the house may be positive if it has historical appeal or negative if it requires expensive upkeep.

## 4 Results

The results for the two-stage quantile regression can be found in Tables 4.1, 4.2, 4.3, 4.4, and 4.5. In general, the variables behave as expected. The size of own house and housing characteristics are found to positively affect housing price across quantiles. The higher quantile houses are, on average, larger and consequently the decreasing effect of an increase in house size is expected. Higher quantile houses appear to value much older homes more than lower quantiles (see house size squared) suggesting a higher willingness to pay for historical appeal. Yard size is valued more for higher quantiles while additional bathrooms are relatively valued by lower quantile consumers. The degree of racial fractionalization is negative and very large, as expected. Other housing and neighborhood characteristics behave as expected and are consistent across quantiles. The strength of spatial dependence increases with housing price, suggesting a larger effect of neighbor house price on own house price for more expensive homes.

Table 4.1: Spatial Autoregressive Results for the 10<sup>th</sup> Quantile

Variable	10 <sup>th</sup> Percentile
$\rho$	0.363 *** (0.043)
School Quality	0.009 *** (0.002)
Onestory	0.036 *** (0.008)
Air	0.097 *** (0.015)
Fire	0.049 *** (0.007)
Fullbath	0.095 *** (0.010)
Partbath	0.043 *** (0.010)
Age of House	-0.678 *** (0.052)
Age Squared	0.181 *** (0.044)
House Size	0.391 *** (0.035)
House Size Squared	-0.036 *** (0.008)
Yard Size	0.098 *** (0.009)
Deck	0.076 ** (0.033)
Taxes	0.003 ** (0.002)
Pollution	0.000 (0.000)
Racial Frac.	-0.089 (0.059)
Average Income	0.000 *** (0.000)
Crime	0.000 *** (0.000)
Neighbor House Size	-0.012 (0.019)
constant	7.020 *** (0.211)
$R^2$	0.5123

Table 4.2: Spatial Autoregressive Results for the 25<sup>th</sup> Quantile

Variable	25 <sup>th</sup> Percentile
$\rho$	0.334 *** (0.024)
School Quality	0.010 *** (0.001)
Onestory	0.020 *** (0.007)
Air	0.068 *** (0.008)
Fire	0.044 *** (0.004)
Fullbath	0.076 *** (0.006)
Partbath	0.039 *** (0.006)
Age of House	-0.639 *** (0.051)
Age Squared	0.233 *** (0.030)
House Size	0.300 *** (0.031)
House Size Squared	-0.015 ** (0.006)
Yard Size	0.118 *** (0.010)
Deck	0.045 *** (0.017)
Taxes	0.001 * (0.001)
Pollution	0.000 (0.000)
Racial Frac.	-0.126 *** (0.032)
Average Income	0.000 *** (0.000)
Crime	0.000 *** (0.000)
Neighbor House Size	0.003 (0.017)
constant	7.247 *** (0.211)
$R^2$	0.5656

Table 4.3: Spatial Autoregressive Results for the 50<sup>th</sup> Quantile

Variable	50 <sup>th</sup> Percentile	
$\rho$	0.403	***
	(0.024)	
School Quality	0.010	***
	(0.001)	
Onestory	0.036	***
	(0.005)	
Air	0.053	***
	(0.008)	
Fire	0.044	***
	(0.004)	
Fullbath	0.072	***
	(0.004)	
Partbath	0.034	***
	(0.005)	
Age of House	-0.678	***
	(0.045)	
Age Squared	0.323	***
	(0.033)	
House Size	0.278	***
	(0.020)	
House Size Squared	-0.007	**
	(0.003)	
Yard Size	0.135	***
	(0.007)	
Deck	0.038	***
	(0.024)	
Taxes	0.000	
	(0.001)	
Pollution	0.000	
	(0.000)	
Racial Frac.	-0.176	***
	(0.028)	
Average Income	0.000	***
	(0.000)	
Crime	0.000	***
	(0.000)	
Neighbor House Size	-0.022	*
	(0.011)	
constant	6.840	***
	(0.191)	
$R^2$	0.5776	

Table 4.4: Spatial Autoregressive Results for the 75<sup>th</sup> Quantile

Variable	75 <sup>th</sup> Percentile	
$\rho$	0.448	***
	(0.029)	
School Quality	0.011	***
	(0.001)	
Onestory	0.035	***
	(0.007)	
Air	0.051	***
	(0.005)	
Fire	0.039	***
	(0.003)	
Fullbath	0.075	***
	(0.006)	
Partbath	0.031	***
	(0.004)	
Age of House	-0.735	***
	(0.047)	
Age Squared	0.476	***
	(0.040)	
House Size	0.282	***
	(0.026)	
House Size Squared	-0.004	
	(0.001)	
Yard Size	0.154	***
	(0.007)	
Deck	0.065	***
	(0.012)	
Taxes	-0.001	
	(0.000)	
Pollution	0.000	
	(0.000)	
Racial Frac.	-0.182	***
	(0.023)	
Average Income	0.000	***
	(0.000)	
Crime	0.000	***
	(0.000)	
Neighbor House Size	-0.029	*
	(0.015)	
constant	6.494	***
	(0.224)	
$R^2$	0.5814	

Table 4.5: Spatial Autoregressive Results for the 90<sup>th</sup> Quantile

Variable	90 <sup>th</sup> Percentile
$\rho$	0.470 *** (0.025)
School Quality	0.012 *** (0.002)
Onestory	0.030 *** (0.010)
Air	0.042 *** (0.006)
Fire	0.034 *** (0.004)
Fullbath	0.074 *** (0.009)
Partbath	0.023 *** (0.007)
Age of House	-0.645 *** (0.066)
Age Squared	0.532 *** (0.052)
House Size	0.273 *** (0.031)
House Size Squared	0.001 (0.001)
Yard Size	0.168 *** (0.009)
Deck	0.085 *** (0.025)
Taxes	-0.002 *** (0.001)
Racial Frac.	-0.224 *** (0.046)
Average Income	0.000 *** (0.000)
Crime	0.000 (0.000)
Neighbor House Size	-0.011 (0.013)
constant	6.295 *** (0.186)
$R^2$	0.6090



The variable of interest, the effect of an increase in the house size of the nearest neighbors, displays an interesting pattern. Consumers of houses in the 10<sup>th</sup>, 25<sup>th</sup> and 90<sup>th</sup> percentile have an insignificant effect of a decrease in relative status (with a coefficient of (-0.012), (0.003) and (-0.011) respectively) while consumers in the 50<sup>th</sup> and 75<sup>th</sup> percentile have a strong and significant negative effect of (-0.022) and (-0.029). The effect of an increase in absolute status is (0.391) for the 10<sup>th</sup>, (0.300) for the 25<sup>th</sup>, (0.278) for the 50<sup>th</sup>, (0.282) for the 75<sup>th</sup> and (0.273) for the 90<sup>th</sup>. The distribution of the associated effect of a change in neighbor house size on predicted house price by quantile is almost symmetrical.

More specifically, for consumers of houses in the 10<sup>th</sup>, 25<sup>th</sup> and 90<sup>th</sup> percentiles the marginal willingness to pay is -\$275.47, \$65.63 and -\$302.388 for a 100 squarefoot decrease in their nearest neighbors house, respectively.<sup>5</sup> On the other hand, for consumers of houses in the 50<sup>th</sup> and 75<sup>th</sup> the marginal willingness to pay is -\$536.90 and -\$765.43 for a 100 square-foot decrease in their nearest neighbors houses, respectively. For all quantiles, the effect of an increase in relative house size is much weaker than an equivalent increase in absolute house size, which has a marginal willingness to pay of \$8,943.04 for 10<sup>th</sup>, \$6562.88 for 25<sup>th</sup>, \$6784.50 for 50<sup>th</sup>, \$7443.17 for 75<sup>th</sup> and \$7504.72 for 90<sup>th</sup>.

## 5 Conclusion

The associated price change of a decrease in the size of the nearest neighbors' house size on own predicted house price is negative and significant for the middle quantiles. These findings suggest consumers are willing to pay to have a decrease in the size of the nearest neighbors house. However, the willingness to pay for a decline in the house size of the neighbors' is much smaller than the willingness to pay for an increase in own house size. This provides evidence that revealed preferences may not be consistent with some stated

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<sup>5</sup>Willingness to pay calculated by  $\beta_x(\frac{1}{1-\rho})\bar{y}$ , following (Kim et al., 2003a). Because the house size is given in thousands of square feet, the WTP is multiplied by (.1) to see the effect of a change in 100 square feet instead of 1000 square feet.

Table 4.6: Willingness to Pay

Quantile	Marginal Implicit Prices			
	WTP for Increase in Relative Status	Percent of housing price	WTP for Increase in Absolute Status	Percent of housing price
10th%	-\$274.47	0.188%	\$8943.04	6.138%
25th%	\$656.35	0.415%	\$6562.88	4.505%
50th%	-\$536.90	0.369%	\$6784.50	4.657%
75th%	-\$765.43	0.525%	\$7443.17	5.109%
90th%	-\$302.39	0.208%	\$7504.72	5.151%

Note: WTP calculated by  $\beta_x(\frac{1}{1-\rho})\bar{y}$ . Calculations based on an increase in own house size of 100sqft from the mean and neighbors' house size (for both groups of neighbors) effects are calculated based on an increase in size of the average neighbors house by 100sqft from the mean (the average of the three coefficients were used for own house and nearest neighbor house increases).

preference findings, which postulate that individuals care at least as much or more for relative status. Consequently, policy recommendations on the sole basis of stated preferences should be discounted accordingly.

Although the associative effect of a decline in the neighbors' house size is less than the effect of an increase in own house size, it is still significant and varies across the distribution. It appears that it is the consumers of the houses in the middle-to-lower-upper quantile of house price (defined as the 50<sup>th</sup> and 75<sup>th</sup> percentile) who are willing to pay the most to keep up with the Joneses. The lower and upper quantile consumers (defined as the 10<sup>th</sup> and 90<sup>th</sup> percentile, respectively) are willing to pay a significantly lower amount and the effect is insignificant. One plausible explanation is that the lower quantile consumers cannot afford to pursue the Joneses, suggesting the desire for relative status may be a normal good. On the other end of the distribution, it may be that the consumers of the top quantile have already achieved status with respect to the majority of the population and do not value an additional increase. It is the middle-to-upper quantile consumers who have the desire and means to pay for the consumption of status symbols, relative house size in particular.

These results suggest that the representative agent model, although useful, may not tell the entire story. Previous analysis of the change in house size of the nearest neighbors' resulted in an associated effect that is negative and significant, consistent with results found for the 50<sup>th</sup> percentile (Leguizamón, Forthcoming). However, along other points on the distribution, this effect significantly weakens and even changes signs, implying an inconsistent consumption pattern. The associative effect along these other points have potentially important implications regarding preferences and policy recommendations.

# Chapter 5

## Conclusion

This dissertation has addressed the influence that the size of the neighbors' houses have on predicted house price. The associated effect of a change in neighbor house size on predicted house price, how the effect changes when considering different reference groups, and how the effect changes when considering observations along the distribution have been estimated using spatial hedonic models. The analysis of results are framed within the context of behavioral explanations which are then compared to previous results regarding housing consumption behavior and status symbol consumption behavior.

In Chapter 2 Justin Ross and I estimate the change in predicted house price associated with an increase in the average size of the nearest neighbors' house size using a spatial autoregressive model. We use Bayesian analysis and estimate the willingness-to-pay for an increase in neighbor house size of 100 sqft. from the mean to be -\$68 and the willingness-to-pay for an increase in own house size of 100 sqft. from the mean to be \$548. We conduct a similar analysis for neighbor yard size and own yard size and find the marginal changes in willingness-to-pay to be -\$127 and \$177 for an increase in .01 acres respectively.

This suggests that individuals value an increase in absolute house size and yard size significantly more than they value a decrease in the size of the neighbors' house and yard. The debate regarding the importance of relative and absolute consumption to date has

primarily used survey data analysis to capture preferences. These survey data results suggest individuals value their relative consumption of status goods as much or more than their absolute consumption of status goods. Our results are one of the first to attempt to capture revealed preference for relative and absolute consumption in general and the first to conduct this analysis in the housing market in particular.

In Chapter 3 I estimate the associated effect of a change in predicted house price resulting from a change in the house size of various reference groups. I use a spatial autoregressive hedonic model to examine change in predicted house price associated with a change in house size of four different reference groups: nearest neighbors, surrounding neighborhoods, the largest houses in the district and the smallest houses in the district. If an increase in average house size of the given reference group is associated with a decrease predicted house price, it suggests that the “envy effect” dominates the relationship. On the other hand, if an increase in the average house size of the given reference group is associated with an increase predicted house price, this suggests that the “reflected glory effect” dominates.

I find a positive associated effect of an increase in average house size of further neighbors and the smallest houses and a negative associated effect of an increase in the average house size of the nearest and largest houses. This suggests individuals have a dominant envy relationship regarding nearest and biggest neighbor houses and a reflected glory tendency for further and smallest neighbors. The propensity of individuals to have significantly different relationships with various references groups is an idea not addressed in the hedonic literature to date. This analysis highlights the importance of allowing for the possibility that reference group formation is influenced by space.

In Chapter 4 I relax the assumption of the representative consumer and analyze the associated change in predicted house price resulting from a change in the nearest neighbors’ house size over the distribution of housing prices. There is no reason to assume consumers along the distribution exhibit the same magnitude (or direction) of preference. I use a spatial quantile model to estimate the associated effect for the 10<sup>th</sup>%, the 25<sup>th</sup>%, the 50<sup>th</sup>%,

the 75<sup>th</sup>%, and the 90<sup>th</sup>%.

I find consumers of the houses in the lower quantile of housing prices and the upper quantile of housing prices to exhibit an insignificant and small change in predicted house price associated with a change in the house size of the nearest neighbors. It is the consumers of houses in the middle and middle-upper housing price quantile which exhibit a significant and negative associated effect. This suggests that the middle class is influenced by the size of the neighbors' house to a greater degree than the lower and upper classes. One explanation is the the lower class cannot afford to care (suggesting higher relative consumption may be a normal good) and the upper class experiences higher relative consumption on a more global scale. It is the middle and middle-upper consumers who care and have the income to express the preference for a larger relative house with respect to the nearest neighbors.

These findings suggest that policies which redistribute may not be justified on the grounds of increased social welfare. If given the choice to live in a bigger house, but relatively smaller, individuals exhibit the preference to give up some relative size to gain absolute size. Similarly we may expect that individuals prefer to live in a world where their wealth is relatively less but absolutely more compared to a world where their wealth is relatively more but absolutely less (which would be the case under extreme redistribution policies). I find evidence that when individuals engage in an arms race for bigger and better houses, social welfare as measured by revealed preferences through prices, *increases*.

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## Education

Ph.D., Economics, West Virginia University, May 2010

M.A., Economics, West Virginia University, August 2008

B.A., Economics, University of California, Davis, May 2005

## Professional Experience

07/2007-05/2010 **Graduate Student Instructor**, Department of Economics (WVU)

Introduction to Business Statistics (ECON 225)

Principles of Microeconomics (ECON 201)

Principles of Macroeconomics (ECON 202)

Comparative Economic Systems (ECON 454)

## Peer-Reviewed Publications

*"The Influence of Reference Group House Size on House Price."* Leguizamon, Susane, (2010). Real Estate Economics, Forthcoming.

## Working Papers for Peer-Review Journals

*"Revealed Preference for Relative Status: Evidence from the Housing Market."* Leguizamon, Susane and Justin Ross.

*"Who Cares About Relative Status? Applying Quantile Analysis to Revealed Preference Findings."* Leguizamon, Susane and Justin Ross.

*"Spatial Dependence of Health and Education Expenditures across National Governments."* Leguizamon, Susane and J. Sebastian Leguizamon.

*"Rational Discrimination Against Young Women? Evidence from a Labor Market Experiment."* Leguizamon, Susane and Arzu Sen.

## Book Contributions

*"The Case for Growth."* Sobel, Russ and Leguizamon, Susane, 2007. Chapter 1 in *Unleashing Capitalism: Why Prosperity Stops at the West Virginia Border, and How to Fix it*. Edited by Russell S. Sobel.

## Honors and Awards

Vickers Doctoral Student Teaching Award Winner, 2009

Vickers Doctoral Student Research Paper Award Winner, 2009

Jon Vilasuso Doctoral Student Publication Award, 2009

WVU Distinguished Doctoral Student Fellowship Award, 2008-2009

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