Journal of Housing Economics 21 (2012) 55–65

Contents lists available at SciVerse ScienceDirect

Journal of Housing Economics

journal homepage: www.elsevier.com/locate/jhec

Revealed preference for relative status: Evidence from the housing market

Susane J. Leguizamon [a], Justin M. Ross [b,*]

[a] Department of Economics, Tulane University, New Orleans, LA 70125, United States
[b] School of Public & Environmental Affairs, Indiana University, Bloomington, IN 47405, United States

ARTICLE INFO

Article history:
Received 27 April 2009
Available online 28 January 2012

Keywords:
Happiness
Social welfare
Revealed preferences
Fiscal zoning

ABSTRACT

This paper investigates the value individuals place on their relative housing consumption as compared to absolute housing consumption. Using observed housing sales from three Ohio MSAs in 2000, a spatial Durbin hedonic price model provides total marginal willingness-to-pay estimates for both characteristics of housing units and those of its neighbors. Using this revealed-preference approach, we find evidence suggesting individuals do value relative house size, but the absolute effect dominates. For instance, the estimates indicate that if all homes in Columbus were to increase in size by 100 square feet, the net effect of impacts on absolute and relative consumption would be to increase house prices by $605 on average. This stands in contrast to the stated preference literature, which frequently find individuals to be willing to forgo absolute well-being in exchange for relative status gains.

1. Introduction

At least as far back as John Stuart Mill (1806–1873), economists have acknowledged that individuals may compare their personal consumption to the consumption pattern of their peers in deriving utility. 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) would further emphasize the influence of relative status comparisons on individual consumption decisions. With Easterlin (1974) economists started empirically examining the importance of relative status and possible policy implications. More recently Abel (1990), Gali (1994) and Becker et al. (2005) have contributed various models of interdependent utility functions.

If individuals value their relative standing in addition to their absolute level of material well-being, we would expect to see evidence of this preference in markets of goods which symbolize status. Housing consumption is one such good that acts as a reflection on an individual (Cooper, 1974) and is a popularly cited form of positional consumption. If individuals internalize the size of their neighbors' homes into their utility function, this preference should be reflected their marginal willingness-to-pay for an increase in relative house size. If housing prices increase when the size of neighboring homes decline, it provides evidence that individuals value their relative housing consumption. Furthermore, even if there is utility derived from relative consumption gains, the issue must further address whether or not these relative effects outpace gains from improvements in absolute well-being. This is accomplished in a hedonic model by comparing the marginal willingness to pay for a increase in own-house consumption against the housing consumption of neighbors. The estimates from this comparison are then indicative of whether or not increases in housing consumption are positive, zero, or negative-sum games.

This paper tests the demand for absolute and relative status with a revealed preference approach. A spatial hedonic price model is examined to determine whether individuals exhibit a willingness to pay for their relative house size, contributing to the literature in the following two ways. First, an estimate of the importance of relative status

* Corresponding author.
E-mail addresses: sleguiza@tulane.edu (S.J. Leguizamon), justross@indiana.edu (J.M. Ross).

1051-1377/$ - see front matter © 2012 Elsevier Inc. All rights reserved.
doi:10.1016/j.jhe.2012.01.001

based on observed consumer behavior in the housing sector is provided. Second, this relative status effect is compared to the effect of absolute well-being. The dominating effect could have important implications for zoning authorities in setting lot and unit size restrictions. Current literature based on stated preference surveys often suggests that individuals are actually willing to forgo an increase in absolute well-being to experience an increase in relative status. If true, it implies that people might pay more for a small house with even smaller neighbors than a large house surrounded by even larger neighbors. In deriving and comparing the willingness-to-pay for absolute and relative increases, this paper empirically addresses this question with a revealed preference approach.

The results indicate the revealed preference for a relative consumption gain in housing size to be valued by home buyers, but they also suggest that these buyers would be willing to pay more for a increase in absolute consumption than relative. For all three metropolitan areas studied, if all homes increased in size by 100 square feet, the point estimates of the net effect would be to increase housing prices by $489 to $779 on average. These results highlight the need for overlapping analysis between stated and revealed preference approaches to studying the importance of relative status. This paper is organized into four remaining sections. Section 2 reviews the literature, Section 3 describes the methodology and data employed, Section 4 discusses the results and Section 5 concludes.

2. Economics of happiness

Stated preference survey data analysis has consistently yielded the conclusion that individuals value relative status to such an extent that it may be greater than the value of absolute levels of well-being. These surveys typically consist of questions such as "On a scale of 1–7, how happy are you in general?" followed by a question similar to "If your neighbor's 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. Using stated preference survey data Solnick and Hemenway (1998), Johansson-Stenman et al. (2002), Alpizar et al. (2005) and Carlsson et al. (2007) found individuals to prefer having a higher consumption level relative to their peers, even if it meant forgoing a higher level of consumption. Similarly, Luttmer (2005) matches various indicators of well-being with self-reported levels of happiness and finds suggestive evidence of a negative effect from neighbors' earnings on own well-being. Falk and Knell (2004) and Ng (1993) find that relative income is at least as important as absolute income. Clark and Oswald (1996) find that relative wage rates are inversely related to reported job satisfaction. Internationally, Carbonell (2005) and Helliwell and Huang (2005) have found similar results using German income and Canadian job satisfaction data, respectively.

The validity of survey data has, however, been questioned extensively in the literature. Survey data results have been shown to be influenced by factors irrelevant 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 age, and 10 percent of individuals surveyed inaccurately reported the month and day of their birth. Jenkins (1941) discussed biases emanating from the ordering of questions, "leading questions," and the 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). Tanur (1992), Sudman et al. (1996), and Bertrand et al. (2001) have provided further evidence of influence from the order of possible answers given, as well as a respondent's desire to impress the surveyor, either with on-the-spot formulated opinions or true opinions altered out of fear of having a "wrong" opinion. These limitations of survey data suggest that alternative approaches are beneficial to determine the robustness of conclusions drawn from that literature.

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 rises (Daly and Wilson, 2008). 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. When income is treated as exogenous, however, 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.

Frank (1985) describes the desire for relative status in part as a desire for "positional goods."[1] These are scarce goods, characterized by a position within the context of society. The largest house and biggest car, for instance, are both goods for which there exists only one by definition. Even if every individual received a raise, only one individual is the highest paid. Coupled with rising wages, the scarcity of positional goods has caused the emphasis on relative status to grow in recent decades. Frank depicts this as 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 is unchanged but everyone is made worse from reduced leisure time. This desire for position in society may stem from jealousy, envy or are remnants of earlier societies which distributed goods based on relative position. 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, those low levels of housing consumption occur in the rental rather

[1] Hirsch (1976) first coined the term "positional externalities," but Frank has put more emphasis on housing in this context.

Table 1
Variable definitions and sources.

Variable name	Definition
House price[a]	Sale price of house in 2000 dollars
House size[a]	Size of house in thousands of square feet
Yard size[a]	Size of yards in acres
Onestory[a]	Equals 1 if the house is one story, otherwise 0
Air conditioning[a]	Equals 1 if the house has air conditioning, otherwise 0
Fireplace[a]	Equals 1 if house has fireplace, otherwise 0
Full baths[a]	Number of full baths in house
Part baths[a]	Number of partial baths in the house
Age[a]	Age of house in hundreds of years
Deck[a]	Equals 1 if house has a deck, otherwise 0
Proficiency[b]	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[a]	Average amount spent per student by school district in thousands of dollars 2000–2001
Mill rate[a]	Effective mill rate for 2000 Class 1 property(agricultural and residential) in the school district
Pollution[a]	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.[a]	Leik (1966) index of census block racial heterogeneity with 0 being homogenous and 1 being completely heterogenous
Income[a]	Median income of census block in 2000, in thousands of dollars
Crime[a]	Total offenses in the police district, per hundred people, year 2000
Inverse mills ratio[b]	[Heckman (1979)] control for sample-selection bias

[a] Source: obtained from Brasington Ohio housing dataset (Brasington et al., 2005).
[b] Source: Authors' calculation.

than the owner-occupied market. The perception of housing as a status symbol is prevalent in the popular press Frank (2009) and acknowledged in the academic literature as well. (Frank, 2005, p. 137) has made this point specifically with respect to housing size:

> The first choice is between world A, in which you will live in a 4000-square-foot house and others will live in 6000-square-foot houses; and world B, in which you will live in a 3000-square-foot house, others in 2000-square-foot houses. Once you choose, your position on the local housing scale will persist.
> If only absolute consumption mattered, A would be clearly better. Yet most people say they would pick B, where their absolute house size is smaller but their relative house size is larger. Even those who say they would pick A seem to recognize why someone might be more satisfied with a 3000-square-foot house in B than with a substantially larger house in A.

As such, housing provides an excellent tool to study the nature of relative status symbols. The only other attempt we are aware of is Turnbull et al. (2006), whose analysis relied on a data set of 2111 open market housing sales in East Baton Rouge Parish, Louisiana from 1992 to 1997. In order to test Veblen's (Thorstein Veblen , 1899) conspicuous consumption hypothesis, they model the influence of neighboring house size by creating a set of variables that indicate how much larger or smaller the neighboring houses were within one-half mile. Their results provide estimates that contradict the conspicuous consumption claim by indicating that smaller houses sell at a premium as their neighbor's house size increases. By comparison, this data set covers over 30,000 observations and employs a modified spatial Durbin model. Further details will be discussed in the methodology section, but this will have an advantage in terms of providing estimates of a net effect on the dominance between relative and absolute effects, and it can mitigate certain forms of omitted variable bias.

3. Methodology and data

3.1. Data

We test the model using the Brasington–Ohio housing data set (Brasington, 2001). The data includes over 30,000 observations of year 2000 fair market arm's length real estate transactions for owner-occupied housing in three metropolitan areas. Ultimately the econometric model is estimated separately by MSA classification: Cleveland ($n = 11,063$), Cincinnati ($n = 11,091$), and Columbus ($n = 11,887$).

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 1. House-specific data is used whenever possible, but some variables represent the average within its census block group. The means and standard deviations for each of the variables by MSA is found in Table 2.

3.2. Hedonic regression model

Empirical researchers have increasingly used the hedonic price method to derive an implicit price for goods not directly traded in markets. 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 and unobservable. Observable goods include house amenities such as bedrooms, bathrooms, yard size and architecture, while unobservable goods include non-physical

Table 2
Summary statistics.

	Columbus		Cleveland		Cincinnati	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
ln (sale price)	11.73	0.55	11.61	0.56	11.69	0.54
House size	1.65	0.66	1.57	0.78	1.69	0.71
House size^2	3.17	3.32	3.09	11.96	3.36	3.53
ln (yard size)	9.07	0.59	9.09	0.82	9.25	0.76
W-house size	1.64	0.56	1.57	0.57	1.68	0.54
W-yard size	9.01	0.73	9.06	0.72	9.19	0.74
Maximum house	0.01	0.10	0.00	0.06	0.01	0.08
One story	0.38	0.48	0.29	0.45	0.46	0.50
Air	0.69	0.46	0.17	0.37	0.16	0.37
Fire	0.51	0.58	0.43	0.60	0.54	0.58
Full baths	1.57	0.60	1.29	0.59	1.52	0.61
Part baths	0.56	0.52	0.39	0.54	0.45	0.53
Age	0.33	0.32	0.56	0.29	0.43	0.31
Age^2	0.21	0.35	0.39	0.37	0.28	0.34
Deck	0.01	0.12	0.13	0.34	0.16	0.37
Proficiency	−2.67	15.69	−10.37	19.20	2.41	10.93
Per pupil sending	8.28	0.93	9.06	1.26	7.78	1.28
Mill rate	34.48	6.13	34.73	9.40	32.61	5.34
Pollution	0.20	3.02	0.13	1.05	0.17	1.95
Racial fract.	0.13	0.09	0.16	0.17	0.09	0.08
Income	54.68	23.46	48.79	23.75	53.49	22.13
Crime	0.10	0.06	0.06	0.05	0.06	0.04

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 sample of sufficient size and variation available to consumers, it would be possible to determine the marginal willingness to pay for each attribute using regression analysis.

Hedonic models have been employed to estimate the relationship between house price and hazardous waste sites (Kohlhase, 1991, 1992, 2001), environmental quality (Brasington et al., 2005), air pollution (Smith and Deyak, 1975, 1995, 1999, 2001, 2003) 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.

The standard hedonic model follows the vector form econometric model:

$$y = X\beta + \varepsilon, \tag{1}$$

where y is an $n \times 1$ vector representing the natural logs of housing prices, X is the $n \times m$ vector of m explanatory variables, and ε is normally distributed with constant variance and zero mean.[2] The individual observations consist of an 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.

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 Ohio housing dataset has concluded that the SAR specification is the most appropriate model. Our tests were supportive of this previous literature, and as such we will limit the discussion here to the SAR model. In vector form, the SAR model is specified as

$$y = \rho Wy + X\beta + \varepsilon. \tag{2}$$

Eq. (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. 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 $W \times y$ results in Wy representing the average sale price of a observation's neighbors.

While OLS is biased and inconsistent with the inclusion of Wy in Eq. (2), 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 undermines the implementation of a spatial lag on every independent variable.

The 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*):

$$y = \rho Wy + \beta_0 + \beta_1 hsize + \beta_2 ysize + \beta_3 Whsize + \beta_4 Wysize + X\beta_5 + \varepsilon. \tag{3}$$

The equation specified in (3) will be referred to as Model I, and represents the most direct test of the relative consumption claims regarding housing discussed in the literature review. As a robustness check, 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, because other features might play a role in relative status competition. Spatial lags of neighborhood characteristics tied to each observation were excluded due to collinearity.

Standard economic theory predicts that individual utility increases with consumption, which would be reflected in β_1 and β_2 taking positive values to reflect a greater

[2] See Green and Malpezzi (2003) for more details on the history and advantages of the semi-log functional form in hedonic regressions.

Table 3
Expectations of signs in Eq. (3) for relative and absolute status hypotheses.

Theory	β_1	β_2	β_3	β_4
Relative	+/0	+/0	–	–
Absolute	+	+	0	0

willingness to pay for larger properties and units. To the extent that these individuals desire a greater relative status, β_3 and β_4 will be negative. In other words, if relative status is important to homeowners, a decline in relative house size will result in less utility being derived from consuming the house. Given that preference, a lower willingness to pay should be reflected in the sale price. These expectations are summarized in Table 3.

Comparing β_1 to β_3, and β_2 against β_4, provides 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 3, then 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?". If β_1 is found to be larger than β_3 in absolute value, however, individuals are revealing a stronger preference for absolute consumption. 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.

We employ the Bayesian robust heteroskedastic estimation procedure, as described in (LeSage and Kelley Pace, 2009, p. 146–149). The Bayesian approach carries several distinct advantages that merit implementation in this paper. First, as will be explained shortly, Bayesian models can directly estimate the influence of heteroskedasticity and outliers in the error term. Heteroskedasticity and outliers are problems frequently encountered in housing sales data, but difficult to treat with frequentist methods when spatial interdependence is involved. Secondly, the Bayesian approach allows for some particularly useful model selection tests. Frequentist approaches revolve around testing models against each other and rejecting the null hypothesis of some baseline model, or otherwise comparing model fit statistics. By contrast, the Bayesian approach allows for the estimation of the probability that a particular model is "true" given the data, relative to other competing models. In spatial econometrics, the choice of the appropriate weight matrix for identifying neighboring observations can be critical, particularly when this matrix is applied to both the dependent and independent variables, as in Eq. (3). There are philosophical differences between classical and Bayesian approaches to drawing inference from data, most notably over the use of prior information of previous studies. However, by using "non-informative" priors the resulting coefficient estimates will otherwise mimic frequentist estimates, with some differences remaining due to the direct treatment of outliers and heteroskedastic error. Letting Z be the control variables specified in Eq. (3), the Bayesian spatial heteroskedastic model is specified as:

$$\begin{aligned}
&y = \rho W y + Z\beta + \varepsilon \\
&\varepsilon \sim N(0, \sigma^2 V) \\
&V_{ii} = v_i, \quad i = 1, \ldots, n, \quad V_{ij} = 0, \ i \neq j \\
&\pi(\beta) \sim N(c, T) \\
&\pi(r/v_i) \sim iid\chi^2(r), \quad i = 1, \ldots, n \\
&\pi(\sigma^2) \sim IG(a, b) \\
&\pi(\rho) \sim U(0, 1)
\end{aligned} \tag{4}$$

The prior distributions are indicated by $\pi()$. 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 reduce their influence within the data set. The hyper-parameter r indicates the degrees of freedom in the χ^2 distribution and is chosen by the researcher. A low value is used to indicate a belief in heteroskedasticity or outliers, while a larger value can indicate a prior belief in homoskedasticity. The prior distributions on σ^2, β, and ρ follow an inverse gamma, normal, and uniform distribution, respectively.

The models were estimated using Matlab v7.8 with the *sar_g* function produced by LeSage and Kelley Pace (2009). Conditional and posterior distributions used for the function were derived in LeSage, 1997 for β, σ and ρ as:

$$\begin{aligned}
&p(\beta|\rho, \sigma, V) \propto N(c^*, T^*) \\
&\quad c^* = (Z'V^{-1}Z + \sigma^2 T^{-1})^{-1}(Z'V^{-1}(I_n - \rho W)y + \sigma^2 T^{-1} c) \\
&\quad T^* = \sigma^2 (Z'V^{-1}Z + \sigma^2 T^{-1})^{-1}
\end{aligned}$$

$$\begin{aligned}
&p(\sigma|\rho, \beta, V) \propto IG(a, b) \\
&\quad a^* = a + n/2 \\
&\quad b^* = (2b + e'V^{-1}e)/2 \\
&\quad e = Ay - Z\beta \\
&\quad A = I_n - \rho W
\end{aligned}$$

$$p(\rho|\beta, \sigma, V) \propto |A| \exp\left(-\frac{1}{2\sigma^2} e'V^{-1}e\right)$$

The function employs the Metropolis within Gibbs sampling procedure, with prior values $c = a = b = 0$ and $T = 10{,}000$ to indicate a noninformative prior, and $r = 4$ for a prior belief of heteroskedasticity.[3] For the dataset

[3] Specifically, "Metropolis within Gibbs Sampling" in SAR models employs the Metropolis-Hastings procedure for ρ and Gibbs sampling for β and σ. See LeSage and Kelley Pace (2009, p. 133–141) for a full and detailed description of the process.

Table 4
Bayesian model probabilities for alternative definitions.

	Cincinnati	Cleveland	Columbus
W_1	$< .01$	$< .01$	$< .01$
W_2	$< .01$	$< .01$	$< .01$
W_3	$< .01$	$< .01$	$< .01$
W_4	$< .01$	$< .01$	$< .01$
W_5	0.01	0.19	$< .01$
W_6	0.82	0.80	$< .01$
W_7	0.17	$< .01$	$> .99$
W_8	$< .01$	$< .01$	$< .01$
W_9	$< .01$	$< .01$	$< .01$

Subscript on W indicates number of nearest neighbors.

and regression models in this paper, convergence diagnostics from both Geweke (1992) and Raftery and Lewis (1992) were employed. These diagnostics for the sampling procedure indicated that the draws achieved a steady state in less than 900 draws for Model I, and a little less than 1000 draws for Model II. The estimates provided in the next section is based on 4000 draws that follow a 1000 draw burn-in.

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 Kelley Pace, 2009, p. 169–173) is employed to determine which definition would be most likely to generate the data. Table 4 demonstrate the results of this estimation for each MSA and indicates that the data in Cleveland and Cincinnati are most likely generated in models which use a weight matrix based upon the six nearest neighbors, whereas Columbus requires seven.

It is likely 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 the 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 which border it are within reasonable driving range.[4] 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. 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 its own structural features and the neighborhood. We assume that the quality of a house is measured by the size, 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 et al., 2005). Per pupil expenditures and proficiency test scores have been shown to be the indicators of school quality that are valued by homeowners (Brasington, 1999), and as a result they are included in the regressions.

The crime rate, degree of racial fractionalization, and level of pollution are expected to decrease the value of the house. 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.

Each set of results also uses the inverse Mills ratio to treat for potential sample-selection issues that might arise on the supply side of the metropolitan housing market (Jud et al., 1994), and was the method employed for this dataset in Brasington et al. (2005). Not all census block groups (CBG) from the metropolitan statistical area appear in the final dataset, with Cleveland having the lowest appearance rate at 58 percent, and Cincinnati the highest at 74 percent.[5] As such, a probit regression to explain the likelihood of the appearance of the CBG in the dataset was estimated. The explanatory variables were the tract-level aggregates analogous to the variables employed in the second stage regression. From this regression, the inverse Mills ratio is calculated as in Heckman (1979) and included as a regressor in the second stage model.

4. Results

The second stage spatial Bayesian heteroskedastic results for Models I and II estimated for each city are presented in Tables 5 through 7. Bayesian regressions estimate a distribution rather than a point estimate for each parameter. A series of descriptive statistics are calculated over the distributions: mean (μ), standard deviation (σ), and the percentiles that define the 95% credibility interval. While statistical significance has no meaning in Bayesian statistics, it is common to examine analogous statistics such as the 95% credibility interval, which is range of values between the 2.5th and 97.5th percentiles. For instance, 95% of the coefficient distribution for yard size on Table 5 lies between 0.065 and 0.086 for Model I, which is significant in the Bayesian interpretation because this range does not contain zero.

[4] In fact, these three MSAs are often referred to as the Greater Cleveland Metropolitan area.

[5] For Cincinnati, 324 of the 441 Ohio census block groups were represented in the data, the highest rate of representation. Columbus was second with 811 of 1256 and Cleveland was last with 400 of 686.

Table 5
Columbus Bayesian spatial AR linear regression posterior estimates.

Dep: ln(hprice)	Model I				Model II			
	μ	σ	$\beta^{.025}$	$\beta^{.975}$	μ	σ	$\beta^{.025}$	$\beta^{.975}$
Intercept	4.176	0.103	3.970	4.377	3.984	0.108	3.768	4.194
House size	0.298	0.011	0.277	0.320	0.296	0.011	0.274	0.319
House size^2	−0.007	0.002	−0.011	−0.003	−0.008	0.002	−0.012	−0.004
ln yard size	0.075	0.005	0.065	0.086	0.089	0.005	0.079	0.099
W-house size	−0.130	0.007	−0.145	−0.116	−0.130	0.010	−0.149	−0.111
W-ln yard size	−0.108	0.009	−0.125	−0.091	−0.104	0.009	−0.121	−0.088
One story	0.016	0.004	0.008	0.024	0.008	0.004	−0.001	0.016
W-onestory					0.043	0.008	0.027	0.058
Air	0.058	0.004	0.050	0.066	0.049	0.005	0.040	0.059
W-air					0.023	0.007	0.009	0.037
Fire	0.035	0.003	0.029	0.041	0.032	0.003	0.025	0.038
W-fire					0.015	0.007	0.002	0.027
Full baths	0.055	0.004	0.047	0.063	0.053	0.004	0.045	0.061
Part baths	0.026	0.004	0.018	0.034	0.026	0.004	0.019	0.034
W-bath					0.011	0.007	−0.003	0.024
Age	−0.210	0.023	−0.256	−0.165	−0.510	0.036	−0.580	−0.441
Age^2	0.153	0.018	0.118	0.188	0.255	0.025	0.206	0.304
W-age					0.336	0.044	0.250	0.423
W-age^2					−0.036	0.033	−0.100	0.028
Deck	0.056	0.032	−0.007	0.119	0.030	0.032	−0.032	0.095
W-deck					0.217	0.070	0.080	0.352
Proficiency	0.001	0.000	0.001	0.001	0.001	0.000	0.001	0.002
Per pupil sending	0.257	0.023	0.213	0.302	0.174	0.023	0.129	0.219
Mill rate	−0.001	0.000	−0.001	0.000	0.000	0.000	−0.001	0.000
Pollution	−0.013	0.190	−0.383	0.363	0.036	0.190	−0.338	0.414
Racial fract.	−0.224	0.028	−0.279	−0.168	−0.128	0.028	−0.182	−0.074
Income	0.010	0.001	0.008	0.013	0.014	0.001	0.011	0.016
Crime	−0.035	0.006	−0.046	−0.024	−0.020	0.006	−0.031	−0.009
Inverse mills ratio	0.001	0.009	−0.017	0.019	0.028	0.009	0.010	0.046
ρ	0.622	0.008	0.607	0.637	0.620	0.008	0.604	0.635
$\bar{R}^2$	0.377				0.377			

Spatial weight matrix is row-stochastic and based on 7 nearest neighbors and prior r-value of 4. Sample size is 11,887 and Gibbs sampling procedure used 4000 draws following a 1000 burn-in.

Columbus estimates for Models I and II are presented in Table 5. Before taking into account the spatial multiplier effect, the 95% credibility interval lies between 0.277 and 0.32, with an expected value of 0.298 for a 1000 square foot increase in house size.[6] An increase in the average size of neighboring houses by 1000 feet, however, reduces the price by −0.13 percent on average, with a 95% credibility interval between −0.145 and −0.116. The sign of this effect is consistent with the expectations of the relative status literature, as summarized in Table 3. However, the magnitude of the relative effect is less than one-half of the absolute effect. It would seem to imply that if neighbors are in a relative status "arms race," that the net effect is not a zero-sum game, but is not as positive-sum as would be the case were relative status not valued.

Elsewhere in Table 5 for Model I, yard size better fits the story of a zero-sum, perhaps even a negative-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.[7] It is interesting this result appears, as zoning laws often mandate 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 with maximum lot size rules as the norm.[8] It could be that yard size is partially capturing 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 further negatively reflected in observed sale prices beyond status effects.

Model II expands Model I in Table 5 by including the spatial lags of the other house-specific control variables, rather than just house and yard size. While much of the relative status literature emphasizes the size of the property, it is reasonable to consider other housing attributes as potential areas for status competition. For instance, it includes a dummy variable if the neighbors have a fireplace, central air conditioner, a deck and a variable for the age of neighbors' housing. The primary consequence this has on the coefficients is to lower the estimates of the own-house size effect slightly. Still, the offsetting effects between

[6] For more accurate qualitative estimates, the spatial multiplier effect must be accounted for, and reflect this in our final Table 8.

[7] The quadratic effect of yard size tended to be collinear with the house size characteristics, so it was excluded.

[8] 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 residential units.

Table 6
Cleveland Bayesian spatial AR linear regression posterior estimates.

	Model I				Model II			
	μ	σ	$\beta^{.025}$	$\beta^{.975}$	μ	σ	$\beta^{.025}$	$\beta^{.975}$
Intercept	5.579	0.114	5.356	5.812	5.346	0.121	5.111	5.584
House size	0.279	0.007	0.266	0.291	0.266	0.006	0.254	0.279
House size^2	−0.007	0.000	−0.008	−0.007	−0.007	0.000	−0.008	−0.006
ln yard size	0.072	0.005	0.061	0.082	0.078	0.005	0.067	0.088
W-house size	−0.091	0.008	−0.106	−0.076	−0.065	0.009	−0.084	−0.047
W-ln yard size	−0.036	0.008	−0.051	−0.020	−0.043	0.008	−0.058	−0.027
One story	−0.008	0.005	−0.018	0.002	−0.012	0.006	−0.023	−0.001
W-onestory					0.003	0.009	−0.015	0.022
Air	0.019	0.006	0.008	0.030	0.023	0.006	0.011	0.035
W-air					−0.023	0.011	−0.045	−0.001
Fire	0.041	0.004	0.033	0.049	0.041	0.004	0.032	0.049
W-fire					0.022	0.008	0.005	0.039
Full baths	0.049	0.005	0.039	0.059	0.047	0.005	0.036	0.057
Part baths	0.050	0.004	0.042	0.059	0.048	0.004	0.040	0.057
W-bath					0.006	0.008	−0.010	0.021
Age	−0.239	0.031	−0.301	−0.175	−0.608	0.038	−0.682	−0.532
Age^2	0.051	0.022	0.006	0.095	0.288	0.028	0.234	0.342
W-age					0.910	0.056	0.800	1.016
W-age^2					−0.585	0.040	−0.663	−0.509
Deck	0.042	0.006	0.030	0.054	0.038	0.006	0.027	0.050
W-deck					0.021	0.013	−0.005	0.048
Proficiency	0.002	0.000	0.001	0.002	0.002	0.000	0.002	0.002
Per pupil sending	−0.069	0.022	−0.112	−0.026	−0.094	0.023	−0.140	−0.048
Mill rate	0.001	0.000	0.001	0.002	0.000	0.000	−0.001	0.000
Pollution	−0.023	0.018	−0.056	0.013	−0.007	0.018	−0.042	0.028
Racial fract.	−0.165	0.014	−0.193	−0.137	−0.100	0.015	−0.130	−0.069
Income	0.013	0.001	0.010	0.015	0.013	0.001	0.010	0.016
Crime	0.010	0.008	−0.007	0.026	−0.001	0.009	−0.017	0.016
Inverse mills ratio	−0.033	0.010	−0.052	−0.014	0.018	0.011	−0.002	0.039
ρ	0.472	0.010	0.452	0.492	0.478	0.010	0.458	0.499
$\overline{R}^2$	0.759				0.767			

Spatial weight matrix is row-stochastic and based on 6 nearest neighbors and prior r-value of 4. Sample size is 11,063 and Gibbs sampling procedure used 4000 draws following a 1000 burn-in.

own-yard size and neighboring yard sizes are fairly close, though at the mean own-yard size is now slightly larger.

The remaining spatial lags of the independent variables suggests there is a positive correlation between the sale price of a house and the amount of amenities in the neighboring homes. These neighboring amenities include having a fire place, full baths, and a deck. 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 age of the house demonstrates an interesting pattern that seems to better fit the relative status literature.

The other neighborhood control variables generally behave as expected in Table 5. Census block median income, per pupil spending, and proficiency scores are positively correlated with housing prices, while the crime rate and degree of racial fractionalization have a negative effect.

Cleveland results are presented in Table 6, and the Cincinnati results are presented in Table 7. While differing somewhat in magnitude from the Columbus results, qualitatively the same inferences are drawn. The relative size of a housing unit matters in all cases, but is smaller than the absolute size. Yard and neighboring yard size are about offsetting in each estimation when both are increased in equal amounts.

To put the estimates into a more quantifiable context, the Model II estimates presented in Table 5–7 are used to calculate the total mean marginal change in willingness-to-pay for a change in house and yard size.[9] These are the variables which zoning authorities often have the most direct influence. As previously discussed, for the full impact in the change of any single coefficient, its impact must account for the spatial multiplier effect. 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. The following identity can be drawn from Eq. (2):

$$S_k = [I_n - W\rho]^{-1}(I_n\beta_k + W\gamma_k)$$

Letting ι_n be a $n \times 1$ vector of ones, then the average total impact will be given by:

$$T = n^{-1}\iota_n' S_k \iota_n$$

So T will be the average total impact to an observation when every observation is changed by Δx_k, and the left hand side expresses this as a sum of the absolute and

[9] See Kim et al. (2003) for a longer exposition on this calculation.

Table 7
Cincinnati Bayesian spatial AR linear regression posterior estimates.

Dep: ln(hprice)	Model I				Model II			
	μ	σ	$\beta^{.025}$	$\beta^{.975}$	μ	σ	$\beta^{.025}$	$\beta^{.975}$
Intercept	4.286	0.100	4.093	4.479	4.066	0.107	3.858	4.277
House size	0.316	0.011	0.294	0.337	0.296	0.011	0.276	0.317
House size^2	−0.008	0.002	−0.011	−0.004	−0.008	0.002	−0.012	−0.005
ln yard size	0.069	0.004	0.060	0.078	0.078	0.004	0.070	0.086
W-house size	−0.131	0.008	−0.145	−0.115	−0.074	0.010	−0.093	−0.056
W-ln yard size	−0.078	0.007	−0.091	−0.065	−0.086	0.007	−0.099	−0.073
Onestory	0.019	0.005	0.009	0.028	0.010	0.005	−0.001	0.020
W-onestory					0.031	0.009	0.013	0.049
Air	0.026	0.006	0.014	0.039	0.032	0.010	0.013	0.051
W-air					−0.011	0.012	−0.034	0.013
Fire	0.063	0.004	0.055	0.071	0.058	0.004	0.050	0.067
W-fire					0.036	0.008	0.020	0.053
Full baths	0.036	0.005	0.026	0.046	0.042	0.005	0.032	0.051
Part baths	0.030	0.005	0.021	0.039	0.037	0.005	0.028	0.046
W-bath					−0.037	0.008	−0.052	−0.022
Age	−0.166	0.029	−0.223	−0.110	−0.594	0.037	−0.666	−0.521
Age^2	0.014	0.025	−0.035	0.063	0.236	0.030	0.177	0.296
W-age					0.669	0.052	0.565	0.770
W-age^2					−0.345	0.043	−0.430	−0.258
Deck	0.056	0.006	0.045	0.068	0.039	0.006	0.028	0.049
W-deck					0.080	0.011	0.059	0.102
Proficiency	0.002	0.000	0.001	0.002	0.002	0.000	0.001	0.002
Per pupil sending	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mill rate	−0.001	0.000	−0.002	0.000	−0.002	0.000	−0.002	−0.001
Pollution	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Racial fract.	−0.353	0.030	−0.412	−0.294	−0.234	0.029	−0.291	−0.175
Income	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Crime	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Inverse mills ratio	−0.084	0.010	−0.103	−0.065	−0.025	0.010	−0.045	−0.006
ρ	0.601	0.009	0.584	0.617	0.613	0.009	0.596	0.630
$\overline{R}^2$	0.381				0.382			

Spatial weight matrix is row-stochastic and based on 6 nearest neighbors and prior r-value of 4. Sample size is 11,091 and Gibbs sampling procedure used 4000 draws following a 1000 burn-in.

Table 8
Mean marginal changes in willingness-to-pay.

	Columbus		Cleveland		Cincinnati	
	MWP	% Change	MWP	%Change	MWP	% Change
Own house size ($\Delta 100ft$)	1133	0.78	671	0.51	1080	0.77
Own house size[a] ($\Delta 100ft$)	−30	−0.02	−18	−0.01	−30	−0.02
Own ln (yard size) (Δ .01 acres)	341	0.23	196	0.15	284	0.20
W-house size ($\Delta 100ft$)	−498	−0.34	−165	−0.13	-271	−0.19
W-ln (yard size) (Δ .01 acres)	−400	−0.27	−107	−0.08	−314	−0.22
Total −Δ house size	605	0.42	489	0.37	779	0.55
Total −Δ yard size	−59	−0.04	89	0.07	−30	−0.02

Note: Calculations based on Model II coefficients reported in Tables 5–7 using Eq. (5).
[a] Source: Authors' calculation.

relative effect. To convert these calculations to dollar changes from the mean, the formula is

$$MWP = \Delta x_k T_k \bar{y}. \tag{5}$$

The $\bar{y}$ represents the mean house price observed in the data for each MSA without the natural log transformation.[10] The ratio of $I_n\beta_k$ to $I_n\beta_k + W\gamma_k$ can be used to determine the portion of the average total impact arising from absolute consumption effects, with the balance coming from relative effects.

The results of the calculations in Eq. (5) are presented in Table 8, which provides for 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 0.42 percent, which is about \$605. As it can be seen, when the houses increased their own size by 100 feet, the absolute effect was to increase their average value by \$1103, but the relative status effect of everyone else increasing their house size by 100 feet resulted in a \$400 decline. By stark contrast, if every house were to

[10] Further discussion of Eq. (5) can be found in Kim et al. (2003).

expand its yard size by 100 feet, the total average effect would be to decrease the value of the mean house price by $59. As Table 8 shows, the Columbus results do not differ considerably from Cleveland and Cincinnati.

5. Conclusion

This paper has estimated the effect of absolute and relative housing consumption in a spatial hedonic model to provide a revealed preference approach to understanding the importance of relative status. If housing can be considered a status symbol, the willingness to pay for an increase in own house size can be taken as the value of an increase in absolute status. Similarly, a decrease in the size of the neighbors' house may be interpreted as the value of an increase in relative status. Survey data literature suggests that individuals value relative status as much or more than absolute status, which would be evident if the willingness to pay for a decrease in the size of the neighbors' house is greater than the willingness to pay for an increase in own house size.

The evidence provided here concurs that individuals do care about both relative and absolute housing consumption, as it has long been suggested by those advocating the existence of positional goods. Unlike much of the stated preference literature, the results of this paper indicate that a increase in absolute house size is valued more than an increase in relative house size, suggesting that individuals value their absolute well-being more than their relative status if all parties are handed an equal increase. More specifically, for the case of Columbus, the willingness to pay for an increase in own house size by 100 square feet from the mean is found to be $1103 while the willingness to pay for a decrease in neighbor house size by 100 square feet from the mean is $400.

Since stated preference surveys often suggest relative status is more important than absolute material well-being, these results highlight the need for further revealed preference approaches. With regards to policy, this result suggests that policies which reduce competition for relative status may be welfare enhancing, but not if it comes at the expense of absolute well being. For instance, zoning authorities should not be so quick to jump to the conclusion that the build up of housing sizes simply results in a "positional treadmill," but can result in general welfare improvements. Future research considering similar revealed preference for income could be similarly informative, perhaps by focusing on revealed preferences in migration or job searching behavior.

With regards to stated preference survey data and revealed preference, the two methods yield similar results on the direction of preference but differ with respect to the strength of the preference. The difference in our findings from those of the survey data analysis literature over the magnitude of preferences for relative status could be due to the many well recognized difficulties in structuring the surveys. 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.

Acknowledgments

We would like to thank Russell Sobel, Chris Coyne, Tim Phipps, Santiago Pinto, and two anonymous referees for their helpful comments and useful feedback.

References

Abel, Andrew, 1990. Asset prices under habit formation and catching up with the Joneses. American Economic Review 80 (2), 38–42.

Alpizar, F., Carlsson, F., Johansson-Stenman, Olaf, 2005. How much do we care about absolute versus relative income and consumption? Journal of Economic Organization 56 (3), 405–421.

Becker, Gary, Murphy, Kevin, Werning, Ivan, 2005. The equilibrium distribution of income and the market for status. Journal of Political Economy 113, 231–248.

Benney, Mark, Riesman, David, Star, Shirley, 1956. Age and sex in the interview. Journal of Sociology 62 (2), 143–152.

Beron, K., Thayer, M., Murdoch, J., 2001. The benefits of visibility improvement: new evidence from the Los Angeles metropolitan area. Journal of Real Estate Finance and Economics 22 (2–3), 319–337.

Bertrand, Marianne, Mullainathan, Sendhil, 2001. "Do People Mean What They Say? Implications For Subjective Survey Data," American Economic Review, Papers and Proceedings, 113 Meeting, pp. 67–72.

Brasington, David, 1999. Which measures of school quality does the housing market value? Spatial and non spatial evidence. Journal of Real Estate Research 18 (3), 395–413.

Brasington, David, "Brasington Housing Data Set. Available from: <www.bus.lsu.edu/brasington/data.htm>.

Brasington, David, Hite, Diane, 2005. Demand for environmental quality: a spatial hedonic analysis. Regional Science and Urban Economics 35 (1), 57–82.

Carbonell, Ferrer A., 2005. Income and well-being: an empirical analysis of the comparison income effect. Journal of Public Economics 89 (5–6), 997–1019.

Carlsson, Fredrik, Johansson-Stenman, Olof, Martinsson, Peter, 2007. Do you enjoy having more than others? Survey evidence of positional goods. Economica 74 (296), 586–598.

Chattopadhyay, S., 1999. Estimating the demand for air quality: new evidence based on the Chiacago housing market. Land Economics 75 (1), 22–38.

Clark, Andrew, Oswald, Andrew, 1996. Satisfaction and comparison income. Journal of Public Economics 61 (3), 359–381.

Cooper, Clare, 1974. The house as a symbol of self. In: Lang, J., Burnette, C., Moleski, W., Vachon, D. (Eds.), Designing for Human behavior. Dowden, Hutchinson & Ross, Stroudsburg, PA.

Daly, Mary, Daniel, Wilson, 2008. Happiness, Unhappiness and Suicide: An Empirical Assessment. Federal Reserve Bank of San Francisco Working Paper 2008–19.

Duesenberry, J.S., 1949. Income, saving and the theory of consumer behavior. Harvard University Press.

Easterlin, R.A., 1974. Does Economic Growth Enhance the Human Lot? Some empirical evidence. In: P.A., David, Reder, M. (Eds.), Nations and Households in Economic Growth: Essays in Honour of Moses Abramovitz. Stanford University Press, Palo Alto, p. 89–125.

Edwards, Allen, 1957. The Social Desirability Variable in Personality Assessment and Research. Dryden, New York.

Falk, Armin, Knell, Markus, 2004. Choosing the Joneses: endogenous goals and reference standards. Scandinavian Journal of Economics 106 (3), 417–435.

Farber, Bernard, 1963. Response falsification and spurious correlation in survey research. American Sociological Review 28 (1), 123–130.

Frank, Robert, 1985. Choosing the Right Pond: Human Behavior and the Quest for Status. Oxford Press, Oxford.

Frank, Robert, When Deficit Isnt a Dirty Word. The New York Times, March 22 2009, p. BU5.

Frank, Robert H., 2005. Positional externalities cause large and preventable welfare losses. American Economic Review 95 (2), 137–141.

Gali, Jordi, 1994. Keeping up with the Joneses: consumption externalities, portfolio choice and asset prices. Journal of Money, Credit and Banking 26 (1), 1–8.

Geweke, John, 1992. Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments. In: Bernardo, J.M., Berger, J.O., Dawid, A.P., Smith, A.F.M. (Eds.), Bayesian Statistics, 4. Oxford University Press, Oxford, pp. 641–649.

Green, Richard K., Malpezzi, Stephen, 2003. A Primer on US Housing Markets and Housing Policy. The Urban Institute Press, Washington, DC.

Heckman, James, 1979. Sample selection bias as a specification error. Econometrica 47 (1), 153–161.

Helliwell, John F., Haifang, Huang, 2005. How's the Job? Well-Being and Social Capital in the Workplace. NBER Working Paper w11759.

Hirsch, Fred, 1976. The Social Limits to Growth. Routledge & Kegan Paul, London.

Hite, D., Chern, W., Hitzhusen, F., Randall, A., 2001. Property value impacts of an environmental disamenity: the case of landfills. Journal of Real Estate and Economics 22 (2–3), 185–202.

Hoehn, J.P., Berger, M.C., Blomquist, G.C., 1987. A hedonic model of interregional wages, rents, and amenity values. Journal of Regional Science, 27 (4).

Hyman, Herbert, Cobb, William J., Feldman, Jacob J., Hart, Clyde W., Herber, Charles, 1954. Interviewing in Social Research. University of Chicago Press, Chicago.

Jaeger, Carol M., Pennock, Jean L., 1961. An analysis of consistency of response in household surveys. Journal of the American Statistical Association 56 (294), 788–810.

Jenkins, John, 1941. Characteristics of the question as determinants of dependability. Journal of Consulting Psychology 5, 164–169.

Johansson-Stenman, Olaf, Carlsson, F., Daruvala, D., 2002. Measuring future grandparents' preferences for equality and relative standing. Economic Journal, 112.

Jud, Donald G., Seaks, Terry G., 1994. Sample selection bias in estimating housing sales prices. The Journal of Real Estate Research 9 (3), 289–298.

Kiel, K.A., McClain, K.T., 1995. House prices during siting decision stages: the case of an incinerator from rumor through operation. Journal of Environmental Economics and Management 28 (2), 241–255.

Kim, C.W., Phipps, T.T., Anselin, L., 2003. Measuring the benefits of air quality improvement: a spatial hedonic approach. Journal of Environmental Economics and Management 45 (1), 24–39.

Kohlhase, J., 1991. The impact of toxic waste sites on housing values. Journal of Urban Economics 30 (1), 1–26.

LeSage, James P., 1997. Bayesian estimation of spatial autoregressive models. International Regional Science Review 20 (1–2), 113–129.

LeSage, James P., Kelley Pace, R., 2009. Introduction to Spatial Econometrics. CRC Press, Boca Raton, FL.

Luttmer, Erzo, 2005. Neighbors as negatives: relative earnings and well-being. Quarterly Journal of Economics 120 (3), 963–1002.

Nelson, A.C., Genereux, J., Genereux, M., 1992. Price effects of landfills on house values. Land Economics 68 (4), 359–365.

Ng, Wang, 1993. Relative income, aspiration, environmental quality, individual and political Myopia- may the rat-race for meeting growth be welfare-reducing. Mathematical Social Sciences 26, 307–350.

Raftery, Adrian E., Lewis, Steven M., 1992. How many iterations in the Gibbs sampler? In: Bernardo, J.M., Berger, J.O., Dawid, A.P., Smith, A.F.M. (Eds.), Bayesian Statistics, vol. 4. Oxford University Press, Oxford, pp. 763–773.

Rosen, Sherwin, 1974. Hedonic prices and implicit markets: product differentiation in pure competition. Journal of Political Economy 82 (1), 34–55.

Smith, V.K., Deyak, T.A., 1975. Measuring the impact of air pollution on property values. Journal of Regional Science 15 (3), 277–288.

Solnick, Sara J., Hemenway, David, 1998. Is more always better? A survey on positional concerns. Journal of Economic Behavior and Organization 37 (3), 373–383.

Sudman, Seymour, Bradburn, Norman, Schwarz, Norbert, 1996. Thinking About Questions: The Application of Cognitive Processes to Survey Methodology. Jossey-Bass, San Francisco.

Tanur, Judith, 1992. Questions About Questions: Inquiries into the Cognitive Bases of Surveys. Russell Sage, New York.

Turnbull, Geoffrey K., Dombrow, Jonathan F., Sirmans, C.F., 2006. Big house little house: relative size and value. Real Estate Economics 34 (3), 439–456.

Thorstein Veblen, orstein Veblen (1899). The Theory of the Leisure Class. University of Chicago.

Weaver, Charles N., Swanson, Carol L., 1974. Validity of reported date of birth, salary and seniority. The Public Opinion Quarterly 38 (1), 69–80.