8-2007

Measuring the Value of Air Quality: Application of the Spatial-Hedonic Model

Seung Gyu Kim
University of Tennessee - Knoxville

To the Graduate Council:

I am submitting herewith a thesis written by Seung Gyu Kim entitled "Measuring the Value of Air Quality: Application of the Spatial-Hedonic Model." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Agricultural Economics.

Seong-Hoon Cho, Major Professor

We have read this thesis and recommend its acceptance:

Roland K. Roberts, Christopher D. Clark, Dayton M. Lambert

Accepted for the Council:
Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

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Measuring the Value of Air Quality:
Application of the Spatial-Hedonic Model

A Thesis
Presented for the
Master of Science
Degree
The University of Tennessee, Knoxville

Seung Gyu Kim

August 2007

Dedication

I dedicate this thesis to my parents.
Without their patience, understanding, support, and most of all love,
the completion of this work would not have been possible.
This work is also dedicated to my wife, Ji Eun Oh,
without whose caring support it would not have been possible.

Acknowledgements

I would like to express my gratitude to all those who gave me the possibility to complete this thesis. I want to thank the Department of Agriculture Economics for giving me permission to commence this thesis. I have to thank my major professor, Dr. Seong-Hoon Cho who taught me much about economics, spatial analysis, and geographic information systems, and many of the ideas presented here were discussed with him. The members of my thesis committee, Dr. Roland K. Roberts, Dr. Christopher D. Clark, and Dr. Dayton M. Lambert, have generously given their time and expertise to better my work. I thank them for their contribution and their good-natured support.

Abstract

The value of air quality improvement following the 1990 Clean Air Act Amendments is estimated at the county level in the lower 48 United States. This study applies a hedonic model to assess the economic benefits of air quality improvement using an instrumental variable approach that combines geographically weighted and spatial autoregression methods to account for spatial heterogeneity and spatial autocorrelation. Positive amenity values of improved air quality are found in five major clusters of areas across Eastern Kentucky and most of Georgia around Southern Appalachian area, the State of Illinois, on the border of Oklahoma and Kansas, on the border of Kansas and Nebraska, and Eastern Texas. The reason for the clusters of significant positive amenity values may be due to the combination of intense air pollution, consumers' awareness of diminishing air quality, and higher marginal benefit of reductions of TSPs in communities with relatively low pollution levels. Surprisingly, negative amenity values of improved air quality are found in the three distinctive clusters of east Virginia, west and central Texas, and southeast Montana. This unexpected result may be explained by worsening air quality with intensive economic growth, greater appreciation in housing prices in those regions, and/or missing variables reflecting regionally specialized economic growth.

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1. Introduction

Air quality directly affects our quality of life. Air pollution is composed of many environmental factors. They include carbon monoxide, nitrates, sulfur dioxide, ozone, lead, secondhand tobacco smoke and particulate matter. Particulate matter, also known as particle pollution, is composed of solid and liquid particles within the air. These particles vary considerably in size, composition and origin. They can be generated from vehicle emissions, tire fragmentation and road dust, power generation and industrial combustion, smelting and other metal processing, construction and demolition activities, residential wood burning, windblown soil, pollens, molds, forest fires, volcanic emissions and sea spray (American Heart Association 2006). The U.S. Environmental Protection Agency (EPA) has reported that tens of thousands of people die each year from breathing airborne particulate matter (EPA 1997a). It was found that overall death rates in the 90 largest U.S. cities rose by 0.5 percent with an increase of 10 ug/m^3 in particles less than 10 micrometers in diameter (Kaiser 2000).

Clean air is considered to be a public good because consumption of clean air by one individual does not reduce the amount of clean air available for consumption by others (Kaul and Mendoza 2003). Pollution causing lack of clean air is typically regarded as a negative externality. A negative externality occurs when the by-product of production or consumption is perceived as a social cost (Lewin 1982). For instance, air pollution created by cars can have harmful health effects on other people; however, drivers of cars usually are not accountable for the costs of the harmful health effects. Negative externalities lead to market failure when the market supplies too much pollution.

Pollution is an example of a market failure that justifies government intervention.

One of the most publicized government interventions associated with negative externalities of air pollution in the United States is the Clean Air Act (CAA), which has been among the most controversial interventions mandated by the U.S. government (Chay and Greenstone 2005). The CAA was imposed to protect and to enhance the nation's air quality in 1963 after air pollution was recognized as a national problem in 1955 by the Air Pollution Control Act. The intention of the CAA was to bring all counties in the United States into compliance with the National Ambient Air Quality Standard by reducing local air pollution concentrations (Greenstone 2004). Amendments in 1970 yielded an entirely rewritten version of the original CAA. The Amendments included new primary and secondary standards. For example, the federal Total Suspended Particulates (TSPs) standards were set at an annual geometric mean not to exceed 75 micrograms of particulates per cubic meter of air (75 ug/m^3) in the long-term, and a 24-hour average of 260 ug/m^3 not to be exceeded more than once per year in the short-term (EPA 2003). The amended CAA set new limits and deadlines on emissions from stationary and mobile sources to be enforced by both state and federal governments. Funds for air pollution research were also increased.

The legislation required the EPA to annually report attainment status for six principal pollutants: ozone, particulate matter, carbon monoxide, sulfur dioxide, nitrogen dioxide, and lead. When counties were non-compliant, the EPA penalized the county by restricting new polluters and regulating pollution control methods of existing polluters. The amended CAA of 1970 was revised again in 1990 as a result of growing environmental concerns. The 1990 CAA amendments (CAAAs) addressed five additional areas: air-quality standards, motor vehicle emissions and alternative fuels, toxic air pollutants, acid rain, and stratospheric ozone depletion. This revision was hailed by supporters as strengthening and improving existing regulations (American Meteorological Society 2007).[1]

Since the inception of the CAA, aggregate emissions of the six principal pollutants have been reduced by 25%, even as U.S. gross domestic product (GDP) increased by 161%, energy consumption increased by 42%, and vehicle miles traveled increased by 149% during the 1970-2002 period. Despite obvious improvements in air quality, no consensus exists on whether the CAA and its amendments are responsible for the improvements, and how much the extent of economic benefits associated with this legislation has created (Chay and Greenstone 2003, 2005; Goklany 1999; Greenstone 2004; Henderson 1996; EPA 1997b).

[1] For instance, a more restrictive annual standard was set for particles in the 0-10 micron range of 40 ug/m^3. In addition, EPA proposed new air quality standards for particulates less than 2.5 micrometers (PM2.5) in diameter by adding a new annual PM2.5 standard set at 15 ug/m^3 and a new 24-hour PM2.5 standard set at 65 ug/m^3, and changing the form of the standard (EPA).

2. Objectives

The objective of this research is to accurately estimate the value of air quality improvement following the 1990 CAAAs at the county level in the lower 48 United States. Reliable estimation of the economic benefits of air quality improvements is useful for policymakers because controversy over the CAAAs originates from the lack of a dependable measure of the value of air quality improvement. This study applies a hedonic model to assess the economic benefits of air quality improvement using an instrumental variable approach that combines geographically weighted and spatial autoregression methods to account for spatial heterogeneity and spatial autocorrelation. This valuation method tests the hypothesis that air quality improvement has economic benefits at the county level and also tests how the measurement of those benefits can be improved by adopting spatial process models. Because this spatial-hedonic model captures spatial variation of the marginal effect of air quality improvement across the country, regional differences in the economic benefits of air quality can be found.

3. Literature Review

Because air quality affects human with various ways, it can be measured with different aspects. For example, air quality can affect human health, so the benefit of improved air quality can be measured by the cost of respiratory disease. Air quality also affects ecosystem, it can be measured by ecological perspective. One method of estimating the economic values of non-market benefits is hedonic pricing approach. Hedonic methods have been gaining popularity in recent years with the application of spatial analysis using geographical information systems (GIS). The hedonic approach estimates the economic benefits of air quality using the functional relationship between observed housing sale prices and air pollution. The effect of air quality on housing sale prices is isolated by controlling for the other factors that influence the housing market. Better control of these other factors allows for better measurement of the economic benefits of air quality improvement.

The hedonic approach to estimating the value of air quality has a long history. Since the enactment of the Clean Air Act and Clean Water Act, a number of hedonic studies have estimated implicit prices for the effect of pollution on property values (Michael, Boyle, and Bouchard 2000). Ridker (1967) and Ridker and Henning (1967) reported the first application of hedonic methods to estimate the effect of air pollution on property values. Since then, many studies have used the hedonic-price model to measure the value of air quality (e.g., Anderson and Crocker 1971; Brucato, Murdoch, and Thayer 1990; Deyak and Smith 1974; Freeman 1974; Graves *et al*. 1988; Harrison and Rubinfeld 1978; Murdoch and Thayer 1988; Nelson 1978; Smith and Deyak 1975; Wieand 1973)

Smith and Huang (1995) conducted a meta-analysis of 37 cross-sectional hedonic studies of the value of air quality. The authors found that a decrease in TSPs of 1 ug/m^3 resulted in a 0.05-0.07% increase in property values. From this small increase, many researches concluded that individuals either place a small value on air quality or the hedonic approach cannot produce reliable estimates of the marginal willingness to pay for air quality improvement (Chay and Greenstone 2005).

Chay and Greenstone (2005) pointed out that these weak results may be explained by two econometric identification problems: omitted variables in the housing price-air pollution gradient and heterogeneity across individuals represented by preferences for clean air. They used attainment status as an instrumental variable to resolve the identification problem resulting from the endogeneity of TSP in the hedonic price equation. The change between 1970 and 1980 at the county-level was used as the dependent variable in a first-difference model. They claimed their estimates were less sensitive to model specification than estimated from the cross-sectional and fixed effects models typically used in hedonic studies.

Although their findings resolve the two econometric identification problems, i.e., omitted variable and endogeneity, there are more issues associated with spatial heterogeneity and spatial autocorrelation that need to be addressed to improve the findings. While the conceptual logic of the hedonic price approach for capturing the impacts of air quality appears sound, hedonic models are often criticized with regard to spatial autocorrelation caused by spatial dependence (Beron *et al*. 2004). Furthermore, urban and regional economists have long challenged the control of spatial heterogeneity (Adair, Berry, and McGreal 1996; Goodman and Thibodeau 1998). Spatial heterogeneity means that structural relationships are not stable over space. Spatial dependence is a systematic spatial variation that results in observable clusters or a systematic spatial pattern (Florax and Nijkamp 2003). The development and application of consistent and efficient estimators to capture spatial dependence and spatial heterogeneity has been an important part of the spatial econometric/statistics literature over the last few decades (e.g., Anselin 1998a, 1998b; Can 1990, 1992; Casetti 1972; Cliff and Ord 1973; Dubin 1992, 1998; Fotheringham and Brunsdon 1999; Getis and Ord 1992; Kilkenny and Thisse 1999; LeSage 1997; Leung *et al*. 2000; McMillen 1992, 2003; Monchuk 2003; Monchuk and Miranowski 2004; Tse 2002).

Modeling spatial heterogeneity using regional indicator variables is one approach to account for heterogeneity caused by spatial units. This technique is effective, but has some limitations. Critics suggest that this approach captures unobserved heterogeneity at a regional level but not at local level (Clapp 2003, 2004). Instead, researchers have proposed a so-called geographically weighted regression (GWR) as a way of accounting for the potential presence of spatial heterogeneity in a hedonic model. GWR is a local regression technique accommodating spatial heterogeneity by locally weighted regression as first proposed by Cleveland and Devlin (1988) that is similar to other semi-parametric methods which allow coefficients to vary across space (Clapp 2003, 2004; McMillen 2003).

While, in general, GWR appropriately controls spatial heterogeneity, the residual of the GWR is not free from spatial error autocorrelation, causing efficiency loss in standard errors (Anselin 1988a). Housing prices are influenced by a variety of factors, many of which vary by spatial location. Although hedonic models attempt to capture at least some of that variation, there is likely to remain some unexplained spatial variation in price, and therefore spatial correlation of the error terms. If such spatial autocorrelation is not accounted for in the estimation, the results may be misleading (McConnell and Margaret 2005). To address this problem, spatial lag and spatial error models developed by Anselin (1988a) are used to detect and accommodate spatial autocorrelation.

4. Empirical Model

Under the assumption that the housing market is in equilibrium, a household chooses to reside in a location that maximizes utility as follows:

(1) $$Max\, u\left[h_i(a_i, g_i), y - p_i\left(a_i, g_i\right)\right],$$

where $u(\cdot)$ is a continuous twice-differentiable utility function with $u' > 0$ and $u'' < 0$; h_i is the flow of housing services from location *i*, which is a function of a_i (air quality) and g_i (vector of other housing attributes), *y* is household income; and p_i is the price of house *i*, which is also a function of a_i and g_i (Brueckner 1990; Capozza and Helsley). The difference between household income and housing price represents total expenditures on commodities other than housing (i.e., a composite numéraire commodity). The utility gained from consuming housing services subject to a budget constraint generates a quasilinear function with respect to all other goods.

The solution to the consumer's utility maximization problem allows the testing of hypotheses about consumer behavior using the hedonic price model. Although Equation 1 is typically applied to individual housing data, the interest here is in aggregate housing demand for a group of neighbors as follows.

(2) $$Max\, u\left[H_i(A_i, G_i), Y - P_i\left(A_i, G_i\right)\right],$$

Where, H_i is the flow of housing services from county *i*, which is a function of A_i (air quality in county *i*) and G_i (vector of other housing attributes in county *i*), *Y* is average household income in county *i*; and P_i is the median price of house in county *i*, which is also a function of A_i and G_i. The county *i* is used as the unit of observation in identifying groups of neighbors because the CAAAs are imposed at the county level and air quality improvement is measured at that level.

An important methodological issue in air quality hedonic models is the potential endogeneity of air quality improvement. Previous research has suggested endogeneity of the air quality measure in the estimation of hedonic models (e.g., Anselin and Le Gallo 2006; Anselin and Lozano 2007; Chattopadhyay 1999; Chay and Greenstone 2003, 2005). Because local air quality is likely to be correlated with unobserved local economic factors that also affect housing prices, ordinary least square (OLS) estimation likely will yield biased and inconsistent parameter estimates. TSPs attainment status is a potential instrument for the county fixed effect to isolate changes in TSPs that are orthogonal to changes in the unobserved determinants of housing prices (Bayer, Keohane, and Timmins 2006; Chay and Greestone 2005).

Following Chay and Greenstone (2005), a first difference model using an instrumental variable approach is employed to absorb county fixed effects:

(3) $$\Delta P_i = \Delta X_i{}'\beta + \theta \Delta TSP_i + \delta R_i + \alpha R_i * \Delta TSP_i + e_i$$

(4) $$\Delta TSP_i = \Delta X_i{}'\Pi_X + Z_{95i}\Pi_Z + \upsilon_i \, ,$$

where ΔP_i is the change in the logarithm of housing price, ΔX_i is the change in a vector of observed characteristics, ΔTSP_i is the change in TSPs density in tons per square mile between 1990 and 2000, R_i is a vector of regional dummy variables to control for region-specific heterogeneity, $R_i * \Delta TSP_i$ is a vector of their interactions with the change in TSPs, Z_{95i} is the mid-decade TSP attainment status in county *i* for 1995, and e_i and υ_i are the unobserved determinants of housing prices and TSPs levels respectively. For identification, the least-squares estimator of θ requires $E\left[e_i \cdot \upsilon_i\right] = 0$.

Mid-decade TSP attainment status (Z_{95i}) is used as an instrument in Equation 4 to account for the potential endogeneity of TSP in Equation 3. Chay and Greenstone (2005, pp. 401-406) explained that mid-decade attainment status is a better candidate instrument than the attainment designation at the beginning of the decade because a smaller time window is available for general equilibrium responses to affect the composition of households and houses and because mid-decade attainment status is also uncorrelated with most observable determinants of housing prices, including economic shocks. TSP reduction is attainment counties and nonattainment counties are -34.64 and -2.11, respectively.

Anselin and Lozano (2007) raised another important issue regarding spatial structure of house values in the hedonic model. They establish that the hedonic model should take account for the effects of neighboring housing values with a spatial lag model. Without accounting for spatial lag effects, inference may be compromised because spatial error autocorrelation produces inefficient standard errors of the estimates, while spatial lag dependence yields inconsistent and biased estimates (Anselin 1998a). To correct for spatial error autocorrelation, the hedonic model of Equation 3 can accommodate the potential spatial lag dependence of housing value:

(5) $$\Delta P_i = \rho W \Delta P_j + \Delta X_i{}' \beta + \theta \Delta T_i + \delta R_i + \alpha R_i * \Delta T_i + \xi_i$$

where W is a spatial weight matrix which can be measure as a default minimum threshold distance, ρ is spatial autoregressive coefficient explaining spatial lag dependence between housing prices ($W\Delta P_i$). An instrumental variable (or two-stage least squares regression) approach is used to estimate Equation 5 (Anselin 1988a). The first stage entails regressing the spatial lag of the differenced housing prices on all exogenous variables, and their first and second spatial lags:

(6) $$W\Delta P_i = \delta_1 \Delta\tilde{X}_i + \delta_2 W\Delta\tilde{X}_i + \delta_3 W^2 \Delta\tilde{X}_i + \mu_i ,$$

where $\Delta\tilde{X}_i$ is a matrix containing $\Delta X_i, \Delta T_i, R_i,$ and $R_i * \Delta T_i$. For the second stage, Equation 5 is estimated using the predicted value of $W\Delta\hat{P}_i$ from the Equation 6.

In order to account for potential spatial heterogeneity at the local level, GWR is applied to Equations 3 and 5. Equation 3 with GWR can be specified as:

(7) $$\Delta P_i = \Delta\tilde{X}_i{}'\beta(u_i, v_i) + \varepsilon_i .$$

where ε_i is a random disturbance term; and (u_i, v_i) are location coordinates. Given predicted values of $W\Delta\hat{P}_i$ from Equation 6, Equation 5 can be specified as a geographically weighted regression:

(8) $$\Delta P_i = \rho(u_i, v_i) W\Delta\hat{P}_i + \Delta\tilde{X}_i{}'\beta(u_i, v_i) + \varepsilon_i .$$

The GWR assigns weights to other counties according to their spatial proximity to county i. These weights allow counties in closer proximity to county i to have more influence in the estimation of the local $\hat{\beta}(u_i, v_i)$'s than counties located farther away. An adaptive bi-weight function is used to geographically weight observations. The function is "adaptive" in the sense that the trace of the weight matrix is allowed to expand and contract, conditional upon a given location. The bi-weight function for each w_{ij} is:

(9) $$w_{ij} = \left[1 - \left(d_{ij}/d_{\max}\right)^2\right]^2 \text{ if } d_{ij} \le d_{\max}, \text{ otherwise } w_{ij} = 0,$$

where *j* represents a point in space at which data are observed, *i* represents any point in space for which parameters are estimated, d_{ij} is the Euclidean distance between point *i* and *j*, and $d_{\max}$ in the maximum distance between observation *i* and its *q* nearest neighbors. The weight attributed to regression point *i* is one. Weights attributed to the *j* observations in the neighborhood of *i* are less then one and become zero when the distance between *i* and *j* is greater than $d_{\max}$. Therefore, as d_{ij} increases the influence of observation *j* on local regression point *i* decreases.

A cross-validation approach selects the optimal neighborhood bandwidth *q* as in the cross-validation function:

(10) $$\text{Cross validation} = \min_q \sum_{i=1}^{n} [y_i - \hat{y}_{\neq i}(q)]^2$$

where $\hat{y}_{\neq i}(q)$ is the fitted value of ΔP_i with the observations for point *i* omitted during the fitting process. The bandwidth minimizes the cross-validation function. Thus, in the locally weighted regression model, only counties up to the nearest *q* neighbors are assigned non-zero weights with respect to county *i*. The influence of observations decreases as distance increases from the regression point (u_i, v_i).

To allow for potential correlation between the disturbance terms, the error structures of the Equations 7 and 8 are assumed to have the following structure $\varepsilon_i = \lambda \sum_{j=1, j \neq i}^{n} w_{ij} \varepsilon_j + \xi_i$, $\xi_i \sim iid\left(0, \sigma^2\right)$, where w_{ij} is an element of an *n* by *n* row-standardized spatial weighting matrix, and λ is a spatial error autoregressive parameter. GWR residuals are tested for spatial error autocorrelation using a Lagrange Multiplier

(LM) test (Anselin 1998a). In this analysis a row-standardized inverse distance matrix was used to construct the test statistic

$$LM_{error} = \left(\hat{\boldsymbol{\varepsilon}}'_{GWR}\mathbf{W}\hat{\boldsymbol{\varepsilon}}_{GWR} / \sigma^2_{GWR}\right) / tr\left(\mathbf{W}^2 + \mathbf{W}'\mathbf{W}\right), \quad (11)$$

with *tr* the trace operator. The statistic is distributed as a χ^2 variate with 1 degree of freedom. The null hypothesis is $\lambda = 0$.

To test how spatial heterogeneity and spatial autocorrelation can be mitigated by adopting a spatial process model, models with and without the specifics of the spatial process are estimated and compared, i.e., OLS controlling for regional fixed effects, GWR to account for spatial heterogeneity, and GWR corrected for spatial autocorrelation (GWR-SAR).

Hot spot analysis (Getis-Ord Gi*, Gi statistics) is used to identify the clusters of high and low marginal effect of TSP changes (Ord and Getis1995). This analysis is implemented by looking at each county within the context of neighboring counties. The distance for identifying neighboring counties is calculated from Geoda 0.9.5-i as a default minimum threshold distance (Anselin 2005). The local sum of the marginal effects of TSP changes for a county and its neighbors is compared proportionally to the sum of all counties. When the local sum is much different than the expected local sum, and that difference is too large to be the result of random chance, those counties with much different local sum are identified as clusters of high and low marginal effect of TSP changes (ESRI 2007). Once the clusters are mapped, marginal effects of TSP are overlaid on the Gi statistics map. By doing so, only negative marginal effects among clusters of negative Gi statistics and only positive marginal effects among clusters of positive Gi statistics are mapped.

5. Study Area and Data

The study area includes the entire continental United States which consists of 3,107 counties and county equivalents in the 48 States and District of Columbia. After excluding missing observations from five counties, 3,102 counties are used in the empirical model. The empirical model uses four county-level datasets in a geographical information system (GIS): (a) TSPs (PM-10, which includes only those particles with aerodynamic diameter smaller than 10 um) attainment status for 1995 and TSPs emission density in 1990 and 2000 from the U.S. EPA (EPA 2006), (b) socioeconomic and housing variables from the 1990 and 2000 County and City Data Books (2003) and the GeoLytics Census CD, (c) 1999 Natural Amenities Scales and Rural-Urban Continuum Code from USDA Economic Research Service (McGranahan 1999), and (d) regional dummy variables and their interactions with the TSP variable based on Census Bureau Regions and Divisions with State Federal Information Processing Standard (FIPS) codes (U.S. Census Bureau 2007). All of these variables are joined together by means of county FIPS codes.

TSP nonattainment counties in 1995 are presented in Table 1. At least one county could not meet the annual TSPs standard in 21 states. California had the most number of counties in nonattainment (15), followed by Colorado with 12, Arizona with 8, Montana with 7, and Oregon with 6. It is somewhat unexpected that Montana and Oregon, states with relatively small populations, contain a number of nonattainment. It is also a little surprising that the states in the Southeast with rapidly growing populations, i.e., Georgia, are free of nonattainment counties.

Simple descriptive statistics for county-level TSPs emission density, and socioeconomic and housing variables for 1990 and 2000 are presented in Table 2. All dollars values are converted to year 2000 dollar. Over the period of 1990-2000, TSPs emission density decreased from 19.4 tons/mile^2 to 15.9 tons/mile^2. During the same period, median housing value increased from \$54,183 to \$84,145, unemployment rate dropped from 7.17 to 4.72, and the percentage of the population with high school and college graduates increased from 0.70 and 0.13 to 0.77 and 0.22, respectively.

The natural amenities scale is a measure of the physical characteristics of a county area that enhance the location as a place to live (ERS 1999), The scale was constructed by ERS (1999), combining six measures of climate, topography, and water area that reflect environmental qualities most people prefer. These measures are warm winter, winter sun, temperate summer, low summer humidity, topographic variation, and water area. The 1993 Rural-urban continuum code, also constructed by ERS (2003), is used to categorize counties into groups that go beyond a simple metro-nonmetro dichotomy. The codes form a classification scheme that distinguishes metropolitan counties by the population size of their metro area, and nonmetropolitan counties by degree of urbanization and adjacency to a metro area or areas.

Census region is used to create regional indicator variables to account for heterogeneity caused by spatial units. Census regions are groupings of states that subdivide the United States (U.S. Census Bureau 2007). Because the census regions represent the nation's macro-scale subnational regions, it is reasonable to assume the regional indicator variables using the census region capture non-stationarity between housing value and housing attributes. According to the U.S. Census Bureau (2007), the continental United States is delineated as four regions which consist of nine divisions:

New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific. Eight regional dummy variables are created to capture the regional variation in housing value to account for spatial heterogeneity. The West South Central division is chosen as the reference region. Figure 1 shows census regions and divisions of the United States.

Definitions and descriptive statistics for the variables used in the model are presented in Table 3. The change of emissions of TSPs in tons per square mile is chosen to reflect air quality improvement because the TSPs are the most visible form of air pollution and have the most pernicious health effects of all the pollutants regulated by the CAAAs (Chay and Greenstone 2003; Graves *et al*. 1988; Palmquist and Israngkura 1999). Change of median housing value during the 1990s, instead of median housing value for 1990 or 2000, is used as a dependant variable because first-differencing the data absorbs the county permanent effects under the framework of the hedonic model (Chay and Greenstone 2005). Accordingly, all explanatory variables except natural amenity scale, regional dummy variables, and their interactions with TSP are measured as changes between 1990 and 2000.

One of the concerns of using aggregate housing value at the county-level instead of at the individual level is that the aggregate values may mask considerable spatial heterogeneity within the county that may be critical to measuring attributes of housing value. This spatial heterogeneity may induce some bias. Nevertheless, Chay and Greenstone (2005) assert that the aggregation to the county level may not be an important source of bias for two reasons noting that their estimates, generated by aggregation to the county level, are similar to the results based on more disaggregated data summarized in

Smith and Huang (1995). First, the aggregation does not lead to the loss of substantial variation in TSPs, thus the bias generated by the spatial heterogeneity of TSPs within the county should not be significant. Using the availability of readings from multiple monitors in most counties, they find that only 25 percent of the total variation in 1970–80 TSPs changes is attributable to within-county variation, Second, since there are substantially fewer monitors than disaggregated data, i.e., at the census tract level or the individual house level, disaggregated analysis introduces inference problems that a more aggregated county-level analysis avoids.

The changes in socioeconomic conditions that may affect changes in housing values are represented by changes in income, unemployment, employment in manufacturing, population density, white ratio, senior ratio, population with high school degree, population with college degree, urban population ratio, poverty ratio, and per capita tax (County and City Data Books 2003). The changes in housing characteristics that may have effects in the change of housing value include the changes in the percentage of houses built in last 10 years, percentage of houses built 10-20 years ago, percentage of houses built more than 40 years ago, percentage of houses without plumbing, percentage of vacant houses, and percentage of owner-occupied houses. The natural environment and regional characteristics that may influence housing values consists of the natural amenity scale and rural-urban continuum code. These variables are chosen on the basis of the general hedonic specification and the framework laid out in Chay and Greenstone (2005).

Changes in the level of TSPs emission densities between 1990 and 2000 are mapped in Figure 2. During this period, TSPs emission declined by 0.17 (tons/mile^2) over the continental United States. The TSPs emission density decreased the most in Kings County, New York (226.9 tons/mile^2) whereas it increased most in Convington City, Virginia (227.2 tons/mile^2). Figure 3 shows the change in median housing price (2000 dollars) during the 1990s. The median housing price doubled in 188 out of 3,102 counties (6%). It increased between 50% to 100% in 1,842 counties (59%), establishing two major clusters in the eastern and the western regions. It increased by less than 50% in 1,019 counties (33%). It dropped in 53 counties during the 1990s.

6. Empirical Results

The overall performances of the three models in the second stage of 2SLS are compared in Table 4. The LM test for spatial error shows that the OLS and GWR residuals are spatially autocorrelated. The spatial error LM test based on the GWR residuals is reduced by 80% compared to the LM test based on the OLS residuals. However, spatial autocorrelation still remained in the GWR residuals. Finally, the null hypothesis of no spatial error autocorrelation could not be rejected in the GWR-SAR. The adjusted R^2 for the GWR-SAR is 0.85, higher than for the OLS (0.53), and slightly lower than for the GWR (0.87) regression. The error sum of squares for the GWR-SAR is 14.4, lower than for the OLS (47.0) and slightly greater than for the GWR (13.5). The global *F*-test comparing the global and local models confirms that the local models of GWR and GWR-SAR outperform the global model of OLS. The overall fit of the GWR model is slightly better than the GWR-SAR model. However, the GWR-SAR model effectively controls for spatial error autocorrelation, which is still present in the GWR residuals.

Results for the change in TSPs pollution and other variables that control the effects on housing price for the three models are presented in Table 5. The effect of the TSP variable is not trivial due to interactions with the regional fixed effects, and more insight can be gained by calculating the marginal effect of TSPs variable by regions. The marginal effects of TSPs on housing price across all regions for the three models are presented in the Table 6.

The marginal effects of TSPs in the OLS model are insignificant. The median value for the marginal effect of overall area from the GWR model is negative and varies between -0.837 and 0.811, showing significant spatial variation of the marginal effect of

TSP. The marginal effects of the GWR-SAR model are also negative but the variation is smaller than that of GWR, between -0.705 and 0.569. The GWR model and GWR-SAR model consistently show that the marginal effect of the economic benefit of air quality improvement is higher in Middle Atlantic, East North Central, South Atlantic, and East South Central regions than the average at the median value.

The estimates from the GWR-SAR were used to identify clusters of areas where the marginal effects of TSPs on housing price are significantly different from others. The spatial clusters of significant marginal effects at the level of 5% are mapped using the Getis-Ord Gi* statistics (Ord and Getis 1995). The threshold distance of 1.46 decimal degrees (approximately 100 miles) is used. This distance is calculated from Geoda as a default minimum threshold distance for identifying neighborhood. Once the clusters are mapped, marginal effects of the TSPs are overlaid on the Gi statistics map. By doing so, only negative marginal effects among clusters of negative Gi statistics and only positive marginal effects among clusters of positive Gi statistics are mapped in Figure 4.

The clusters of negative marginal effects represent the areas with significant increases in housing prices from reductions in TSPs. The clusters of positive marginal effects represent the areas with significant increases in housing prices from increases in TSPs. There are four major clusters of areas with positive amenity values of air quality improvement. The largest cluster is in East Kentucky and most of Georgia in the Southern Appalachian area. In this cluster, a decrease in TSPs 1 ton/mile^2 increases the average housing price by 2.02%. This implies that marginal implicit price increased air quality by This cluster can be characterized by successful TSPs reductions coupled with a fast growing economy. Georgia is one of the fastest-growing states in the United States, with its gross state product(GSP) and population increases from 149,956 million dollars (1992 constant) and 6.5 million in 1990 to 238,175 million dollars and 8.2 million in 2000, respectively. In spite of vibrant and growing economies around Atlanta, Georgia succeeded in reducing TSP emission by 1.9 tons per square mile which is close to the national average reduction of 2.1 tons per square mile over the period of 1990-2000. As shown in the Table 1, no county in Georgia has TSP nonattainment status in 1995. From 1992 until 2002, Georgia participated in the Southern Appalachian Mountains Initiative (SAMI), a decade long federal-state collaboration aimed at improving air quality in the Appalachian premier natural areas. Positive impacts on the housing market of TSPs reductions in the cluster around Southern Appalachian areas are in accordance with expected benefits (SAMI 2002), which is developing and evaluating potential incentive-based approaches to reducing emissions in the SAMI region.

Another cluster of positive marginal effects of TSPs on housing prices is in few counties in the State of Illinois. In this cluster, a decrease of 1 ton/mile^2 increases the average housing price by 2.17%. Illinois has been regulating motor vehicle inspection and maintenance as one of the sources for air quality control. Regulation motor vehicles for air quality improvement may have raised public recognition and concern about air quality and may have built their significant public preference for impaired air quality.

Another cluster with positive marginal effects of TSPs on housing prices includes areas on the border of Oklahoma and Kansas, on the border of Kansas and Nebraska, and in east Texas. In this cluster, a decrease of 1 ton/mile^2 increases the average housing price by 4.37%. A possible explanation for the cluster is the locational preponderance of oil industry firms drawn by the natural gas basin in and around the area.

Because of intense air pollution from oil processing, residents of the area may be more sensitive about air quality and thus the marginal value of air quality is significantly higher than most other areas. The cluster along the border of Oklahoma and Kansas may be associated with beef processing firms in the area. This industry's emissions produced severe air pollution and damaging enough to affect the area's residents, thus the marginal value of air quality impairment is significantly higher than most other areas.

Another cluster with positive amenity value of air quality improvement is found in a few counties of Montana. This cluster includes Montana Indian reservation Blackfeet. In this cluster, a decrease of 1 ton/mile^2 increases the average housing price by 3.95%. This cluster can be explained by the fact that the marginal benefit of reductions of TSPs is higher in communities with relatively low pollution levels. This finding is consistent with finding by Chay and Greenstone (2005).

Three distinctive clusters with negative amenity values of reductions of TSPs are found in east Virginia, west and central Texas, and southeast Montana. These clusters are more difficult to explain because they contradict the expectation of a positive marginal value of air quality improvement. Our general justification is that these clusters are under intensive economic growth that boosts real estate market diminishing air quality. For example, the cluster in southeast Montana experienced significant deterioration in air quality with a TSP increase of 1.1 ton/mile^2 during the 1990s in concert with booming real estate market in Montana. Although these areas experience significant deterioration of air quality, because the air quality of the areas is still relatively better than average, the worsening air quality with intensive economic growth is found to appreciate housing price. This maybe also partially due to the fact that the explanatory variables that reflect economic growth, i.e., income and unemployment rate, in the model do not control the effect of regionally specialized economic growth on housing price. For example, the cotton industries should control economic growth better for the areas of the central Texas. These variables are missing in the model because of the lack of appropriateness as explanatory variables for the rest of areas.

7. Conclusions

Air quality has been evaluated with the hedonic housing price model by numerous researchers. Many concluded that either individuals place a small value on air quality or the hedonic approach cannot produce reliable estimates of the marginal willingness to pay for air quality improvement. In contrast, Chay and Greenstone (2005) recently concluded that their estimates of the average marginal willingness to pay for clean air are robust. In the midst of these mixed results, this study uses the hedonic model to estimate the value of air quality improvement using an instrumental variable approach that combines geographically weighted and spatial autoregression methods to account for spatial heterogeneity and spatial autocorrelation.

Positive amenity values of improved air quality are found in four major clusters: 1) East Kentucky and most of Georgia around the Southern Appalachian area; 2) a few counties in Illinois; 3) on the border of Oklahoma and Kansas, on the border of Kansas and Nebraska, and in east Texas; and 4) a few counties in Montana. The reasons for the clusters of significant positive amenity values may be different for different clusters. The first cluster is explained by successful TSP reductions coupled with a fast growing economy; the second cluster is explained by awareness of diminishing air quality; the third cluster is explained by higher willingness to pay for improved air quality in an area with poor air quality; and the fourth cluster is explained by higher willingness to pay for maintaining air quality in an area with good air quality. Surprisingly, negative amenity values of improved air quality are found in the three distinctive clusters of eastern Virginia, western and central Texas, and southeastern Montana. This unexpected result may be explained by worsening air quality with a booming real estate market and the inability of the model to capture all of the amenity values of economic growth and the resulting air pollution.

The clusters of positive amenity values of better air quality are found mostly in the eastern regions of the United States. A contributing factor to this phenomenon might be that the relatively small counties in the eastern regions fit the spatial hedonic model better than the larger western counties. Because the locations of specific counties are proxied by county centroids in establishing the weight matrix in the GWR-SAR model, the larger the county, the larger the area the location of the centroid represents. The larger the area represented by the centriod, the wider and the larger the area represented by the optimal bandwidth, the smaller the spatial heterogeneity inherent in the variables. Uneven county sizes may be a disadvantage of spatial analysis with county-level data. Further analysis may compare differences between the states with similar county sizes; one for the western and one for the eastern United States

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Appendix

Table 1. TSP nonattainment counties in 1995

State	County	Count
Arizona	Cochise, Gila, Maricopa, Mohave, Pima, Pinal, Santa Cruz, Yuma	8
California	Fresno, Imperial, Inyo, Kern, Kings, Los Angeles, Madera, Mono, Orange, Riverside, Sacramento, San Bernardino, San Joaquin, Stanislaus, Tulare	15
Colorado	Adams, Arapahoe, Archuleta, Boulder, Denver, Douglas, Fremont, Jefferson, Pitkin, Prowers, Routt, San Miguel	12
Connecticut	New Haven	1
Idaho	Ada, Bannock, Bonner, Power, Shoshone,	5
Illinois	Cook, La Salle, Madison	3
Indiana	Lake, Vermillion	2
Maine	Aroostook	1
Michigan	Wayne	1
Minnesota	Olmsted, Ramsey	2
Montana	Flathead, Lake, Lincoln, Missoula, Rosebud, Sanders, Silver Bow	7
Nevada	Clark, Washoe	2
New Hampshire	Dona Ana	1
Ohio	Cuyahoga, Jefferson	2
Oregon	Jackson, Josephine, Klamath, Lake, Lane, Union	6
Pennsylvania	PA, Allegheny	1
Texas	El Paso	1
Utah	Salt Lake, Utah, Weber	3
Washington	King, Spokane, Thurston, Walla Walla, Yakima	5
West Virginia	Brooke, Hancock	2
Wyoming	Sheridan	1
Total		81

Table 2. Simple descriptive statistics

Definition	Unit	Mean 1990	2000
TSPs emission density	tons/mile^2	14.33	12.16
Median housing value	$	54,182.75	84,145.29
House income	$	23,852.68	32,542.11
Unemployment rate	%	7.17	4.72
Percentage of employment in manufacturing	%	0.19	0.16
Population density	Population/ mile^2	223.52	244.72
Percentage of white	%	0.87	0.85
Percentage of age above 65	%	14.94	14.82
Percentage of persons with high school graduate	%	0.70	0.77
Percentage of persons with college graduate	%	0.13	0.22
Percentage of urban population	%	0.37	0.40
Percentage of persons in poverty	%	0.13	0.14
Percentage of houses built in last 10 years	%	0.20	0.18
Percentage of houses built 10-20 years ago	%	0.24	0.15
Percentage of houses built before 1939	%	0.22	0.18
Percentage of houses without plumbing	%	0.02	0.02
Percentage of vacant house	%	0.15	0.14
Percentage of owner-occupied house	%	0.73	0.74
Per capita taxes	$	501.20	845.35

Table 3. Definitions and descriptive statistics of variables

Variable	Definition	Mean (Std. Dev.)
Dependent variable:		
HVAL	Change in log median housing value from 1990 to 2000 ($)	0.45 (0.18)
Variable of interest:		
TSP	Change in TSPs emission from 1990 to 2000 (tons/mile^2)	2.17 (13.24)
Economic condition variables:		
INCOME	Change in household income from 1990 to 2000	8,683.37 (2,599.22)
UNEMP	Change in unemployment rate from 1990 to 2000 ($)	-2.45 (2.34)
MANF	Change in percentage of employment in manufacturing from 1990 to 2000	-0.03 (0.04)
Demographic and socioeconomic variables:		
POPDEN	Change in population density from 1990 to 2000 (population per square mile)	14.38 (76.83)
WHITE	Change in percentage of population that is white from 1990 to 2000	-0.03 (0.03)
SENIOR	Change in percentage of population above 65 years of age from 1990 to 2000	-0.13 (1.44)
HIGHSCH	Change in percentage of population that is high school graduate from 1990 to 2000	0.07 (0.03)
COLLEGE	Change in percentage of population that is college graduate from 1990 to 2000	0.09 (0.03)

Table 3. Continued

Variable	Definition	Mean (Std. Dev.)
URBAN	Change in percentage of population in urban areas from 1990 to 2000	0.04 (0.11)
POVERTY	Change in percentage of persons in poverty from 1990 to 2000	0.01 (0.03)
Housing variables:		
BLTTEN	Change in percentage of houses built in last 10 years from 1990 to 2000	-0.02 (0.06)
BLTTWTY	Change in percentage of houses built 10-20 years ago from 1990 to 2000	-0.09 (0.05)
BLTOLD	Change in percentage of houses built before 1939 from 1990 to 2000	-0.03 (0.03)
PLUMB	Change in percentage of houses without plumbing from 1990 to 2000	0.00 (0.02)
VACANT	Change in percentage of house that are vacant from 1990 to 2000	-0.01 (0.04)
OWNER	Change in percentage of owner-occupied houses from 1990 to 2000	0.01 (0.02)
Tax and neighborhood variables:		
TAX	Change in per capita taxes ($) from 1990 to 2000	341.47 (1,423.48)
Natural environment:		
AMENITY	Natural amenity scale	0.05 (2.28)
RURAL	Rural urban continuum code	5.59 (2.72)

Table 3. Continued

Variable	Definition	Mean (Std. Dev.)
Regional dummy variables:		
New England	New England = 1, otherwise = 0	0.22 (0.15)
Middle Atlantic	Middle Atlantic = 1, otherwise = 0	0.05 (0.21)
East North Central	East North Central = 1, otherwise = 0	0.14 (0.35)
West North Central	West North Central = 1, otherwise = 0	0.20 (0.40)
South Atlantic	South Atlantic = 1, otherwise = 0	0.19 (0.39)
East South Central	East South Central = 1, otherwise = 0	0.12 (0.32)
Mountain	Mountain = 1, otherwise = 0	0.09 (0.29)
Pacific	Pacific = 1, otherwise = 0	0.04 (0.20)

Table 4. Comparison of overall performance of the three models

Statistic	OLS	GWR	GWR-SAR
Adjusted R square	0.53	0.87	0.85
Error sum of squares	47.0	13.5	14.4
Effective parameters [tr(H)]	37	1,196	1,232
Improvement over OLS		33.5	32.6
degrees of freedom improvement		1,158.8	1,195.0
Global F test for global vs. local models		4.1*	3.5*
Spatial error LM test	896.0	175.0	1.9*

* indicates significance at the 0.01% level.

Table 5. Parameter estimates of the three models

Variable	OLS	GWR			GWR-SAR		
	Coefficient (Std Err.)	Min	Median	Max	Min	Median	Max
Intercept	0.384* (0.202)	-0.522	0.215	0.877	-0.646	0.084	1.332
Air quality variables:							
TSP	0.017 (0.023)	-0.433	0.000	0.246	-0.431	0.000	0.236
TSP*New England	0.011 (0.017)	-0.059	0.000	0.092	-0.067	0.000	0.096
TSP*Middle Atlantic	0.015 (0.022)	-0.046	0.000	0.092	-0.067	0.000	0.096
TSP*East North Central	0.015 (0.021)	-0.101	0.000	0.225	-0.092	0.000	0.225
TSP*West North Central	0.012 (0.015)	-0.181	0.000	0.440	-0.181	0.000	0.431
TSP*South Atlantic	0.015 (0.023)	-0.708	0.000	0.143	-0.691	0.000	0.135
TSP*East South Central	0.008 (0.011)	-0.286	0.000	0.236	-0.270	0.000	0.254
TSP*Mountain	0.016 (0.019)	-0.109	0.000	0.369	-0.098	0.000	0.197
TSP*Pacific	0.014 (0.020)	-0.089	0.000	0.093	-0.067	0.000	0.105

Table 5. Continued

Variable	OLS	GWR			GWR-SAR		
	Coefficient (Std Err.)	Min	Median	Max	Min	Median	Max
Regional dummy variables:							
New England	0.256*** (0.041)	-0.086	0.000	0.364	-0.232	0.000	0.269
Middle Atlantic	0.166** (0.066)	-0.241	0.000	0.364	-0.280	0.000	0.269
East North Central	-0.041 (0.046)	-0.438	0.000	0.364	-0.717	0.000	0.255
West North Central	-0.044*** (0.017)	-0.557	0.000	0.570	-0.695	0.000	0.636
South Atlantic	0.035 (0.068)	-0.266	0.000	0.364	-0.631	0.000	0.316
East South Central	-0.008 (0.036)	-0.621	0.000	0.364	-0.782	0.000	0.369
Mountain	-0.084* (0.051)	-1.222	0.000	0.244	-0.443	0.000	0.269
Pacific	-0.069 (0.050)	-0.320	0.000	0.364	-0.219	0.000	0.269
Economic condition variables:							
INCOME	0.014*** (0.004)	-0.018	0.012	0.068	-0.021	0.011	0.064

Table 5. Continued

Variable	OLS	GWR			GWR-SAR		
	Coefficient (Std Err.)	Min	Median	Max	Min	Median	Max
UNEMP	-0.003 (0.003)	-0.094	-0.002	0.052	-0.094	-0.002	0.043
MANF	-0.367** (0.183)	-2.020	0.053	2.904	-1.900	0.060	1.931
Demographic and socio-economic variables:							
POPDEN	0.000 (0.000)	-0.077	0.000	0.046	-0.065	0.000	0.045
WHITE	0.772 (0.529)	-2.515	0.480	4.021	-2.033	0.486	3.644
SENIOR	-0.009*** (0.002)	-0.089	-0.005	0.060	-0.068	-0.006	0.046
HIGHSCH	0.084 (0.419)	-3.465	0.341	2.682	-2.898	0.308	2.310
COLLEGE	-0.405** (0.194)	-3.512	-0.043	3.470	-2.588	-0.005	3.460
URBAN	0.020 (0.048)	-0.734	-0.003	0.966	-0.685	0.002	0.786
POVERTY	-0.067 (0.122)	-2.370	-0.095	2.191	-2.147	-0.083	1.998
Housing variables:							
BLTTEN	0.977*** (0.061)	-0.829	0.697	2.876	-0.626	0.653	2.714

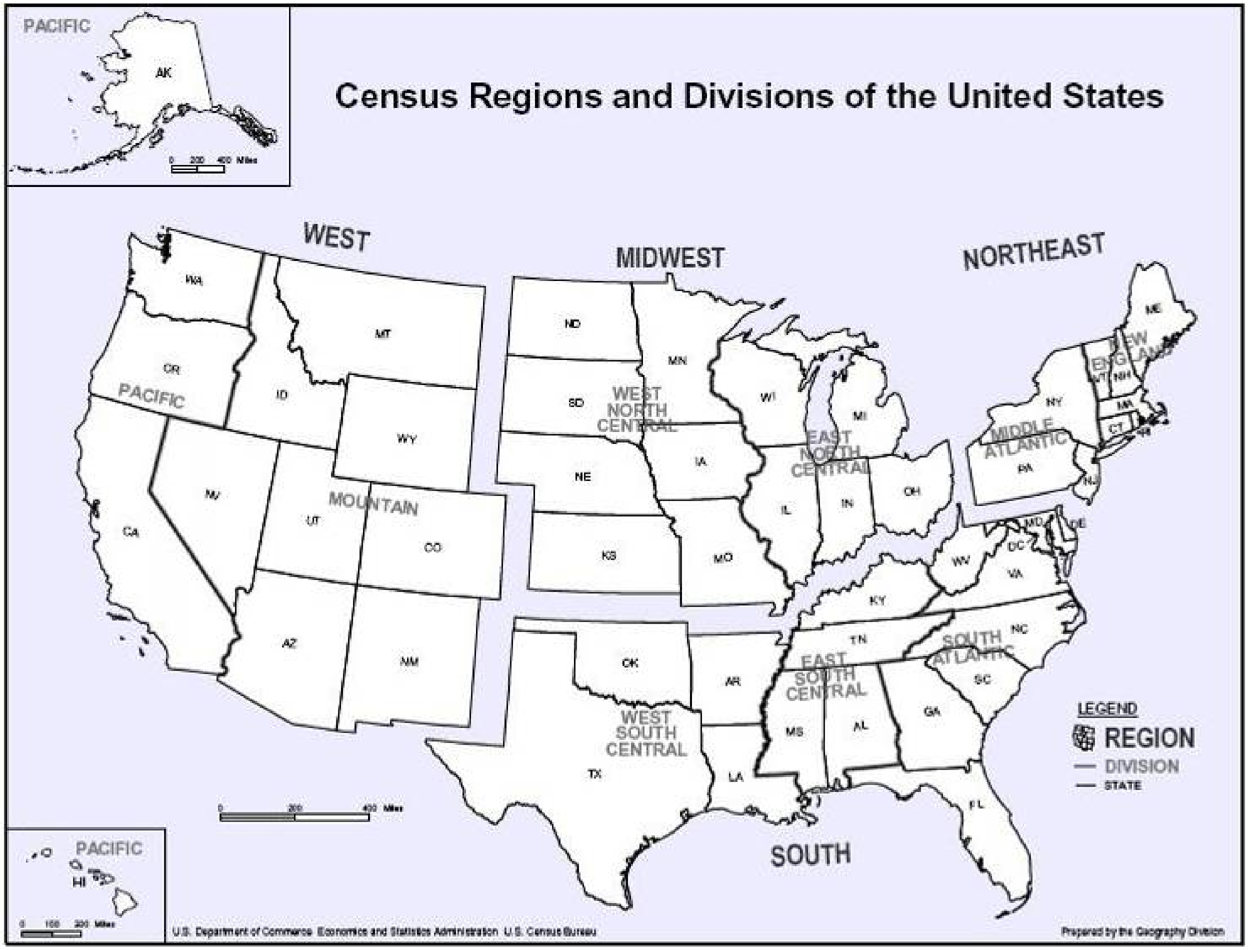
Table 5. Continued

Variable	OLS	GWR			GWR-SAR		
	Coefficient (Std Err.)	Min	Median	Max	Min	Median	Max
BLTTWTY	0.100 (0.186)	-1.702	0.167	2.494	-1.411	0.182	2.161
BLTOLD	-0.060 (0.095)	-2.581	-0.086	3.210	-2.224	-0.065	2.668
PLUMB	-0.394*** (0.146)	-8.940	-0.104	4.874	-7.677	-0.136	4.599
VACANT	-0.522* (0.319)	-4.582	-0.176	2.027	-3.777	-0.217	1.556
OWNER	0.375 (0.947)	-3.398	0.046	4.220	-3.000	0.013	3.849
Neighborhood variables:							
TAX	-0.004** (0.002)	-1.026	-0.025	0.300	-0.860	-0.016	0.201
AMENITY	0.005*** (0.002)	-0.049	0.008	0.093	-0.044	0.007	0.079
RURAL	0.001 (0.008)	-0.080	0.003	0.040	-0.073	0.003	0.034
Spatial variable:							
Spatial lag					-3.183	0.438	2.980

* , **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 6. Marginal effect of 1990-2000 changes in TSPs pollution on change in log housing prices

Region	OLS	GWR			GWR-SAR		
	Marginal Effect	Min	Median	Max	Min	Median	Max
Overall	0.027	-0.837	-0.001	0.811	-0.705	-0.001	0.569
New England	0.045	-0.062	0.000	0.045	-0.064	0.000	0.019
Middle Atlantic	0.051	-0.061	-0.001	0.135	-0.105	-0.001	0.138
East North Central	0.049	-0.161	-0.001	0.811	-0.141	-0.001	0.473
West North Central	0.045	-0.788	0.000	0.274	-0.279	0.000	0.298
South Atlantic	0.051	-0.142	-0.001	0.141	-0.215	-0.001	0.149
East South Central	0.038	-0.837	-0.001	0.102	-0.705	-0.001	0.076
West South Central	-0.142	-0.377	0.000	0.364	-0.369	0.000	0.569
Mountain	0.051	-0.144	0.000	0.225	-0.185	0.000	0.235
Pacific	0.049	-0.079	0.000	0.216	-0.079	0.000	0.181



Source: U.S. Census Bureau

Figure 1. Census regions and divisions of the United States

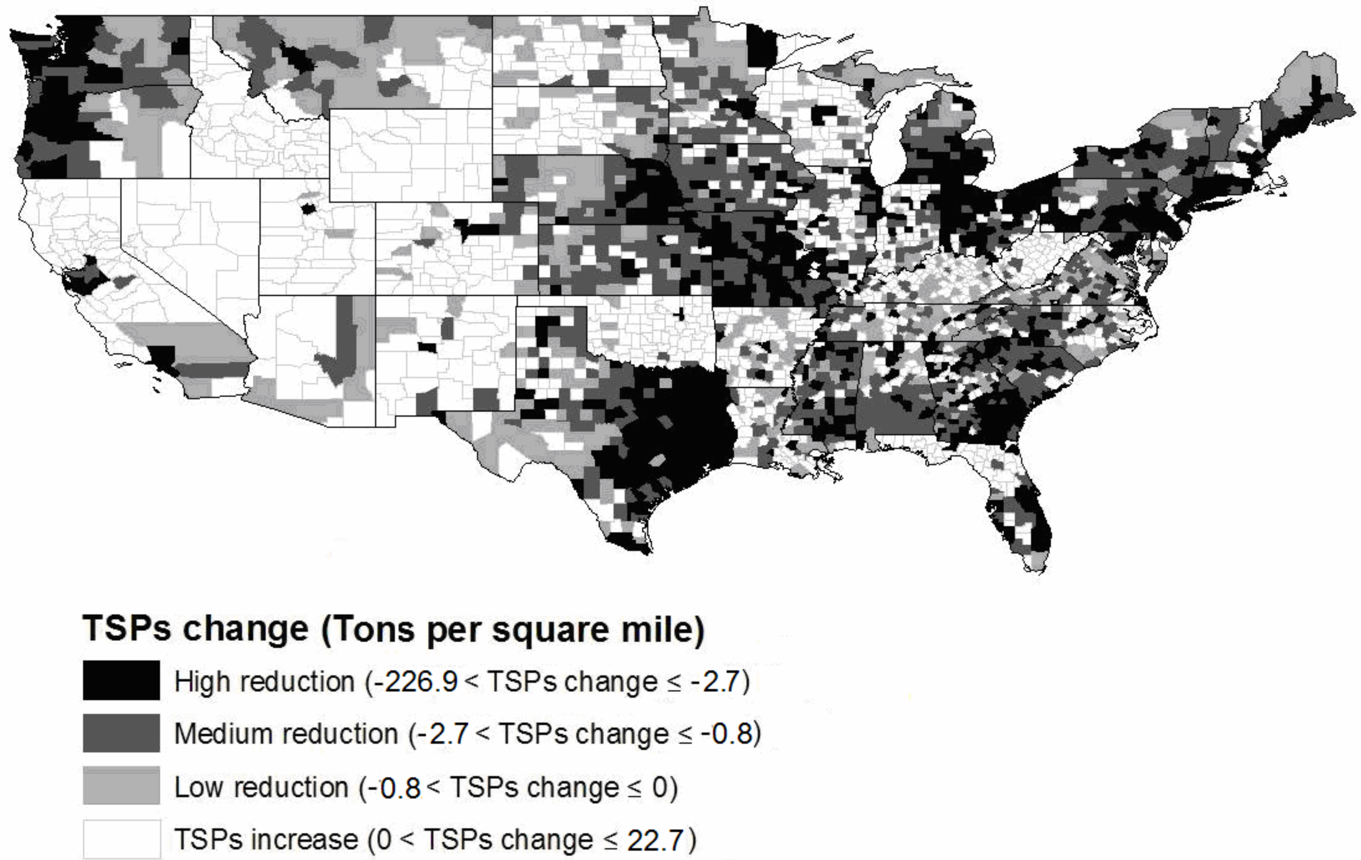


Figure 2. Changes in TSP emission density between 1990 and 2000 (ton/mile^2)

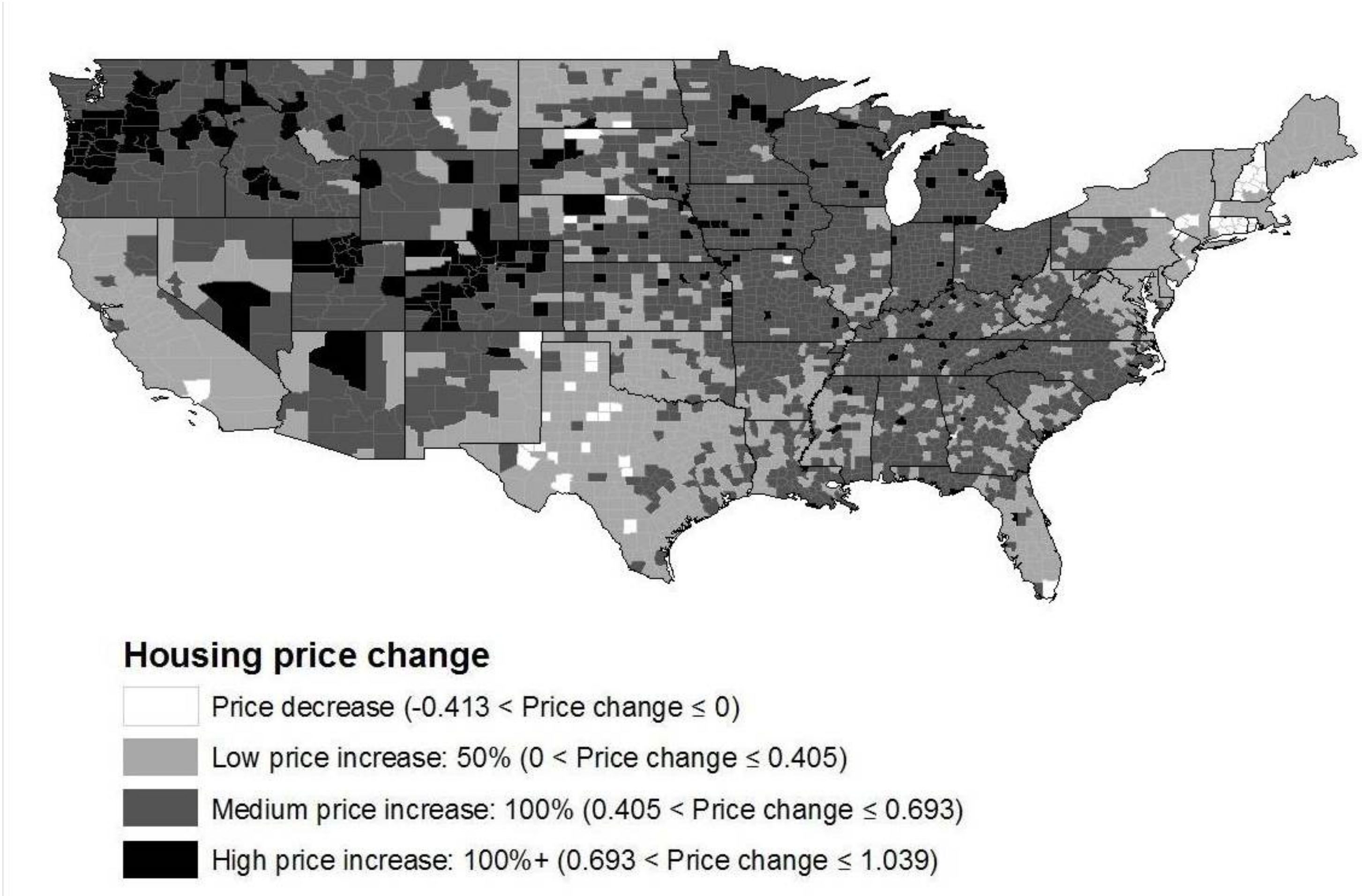


Figure 3. Changes in log housing price between 1990 and 2000

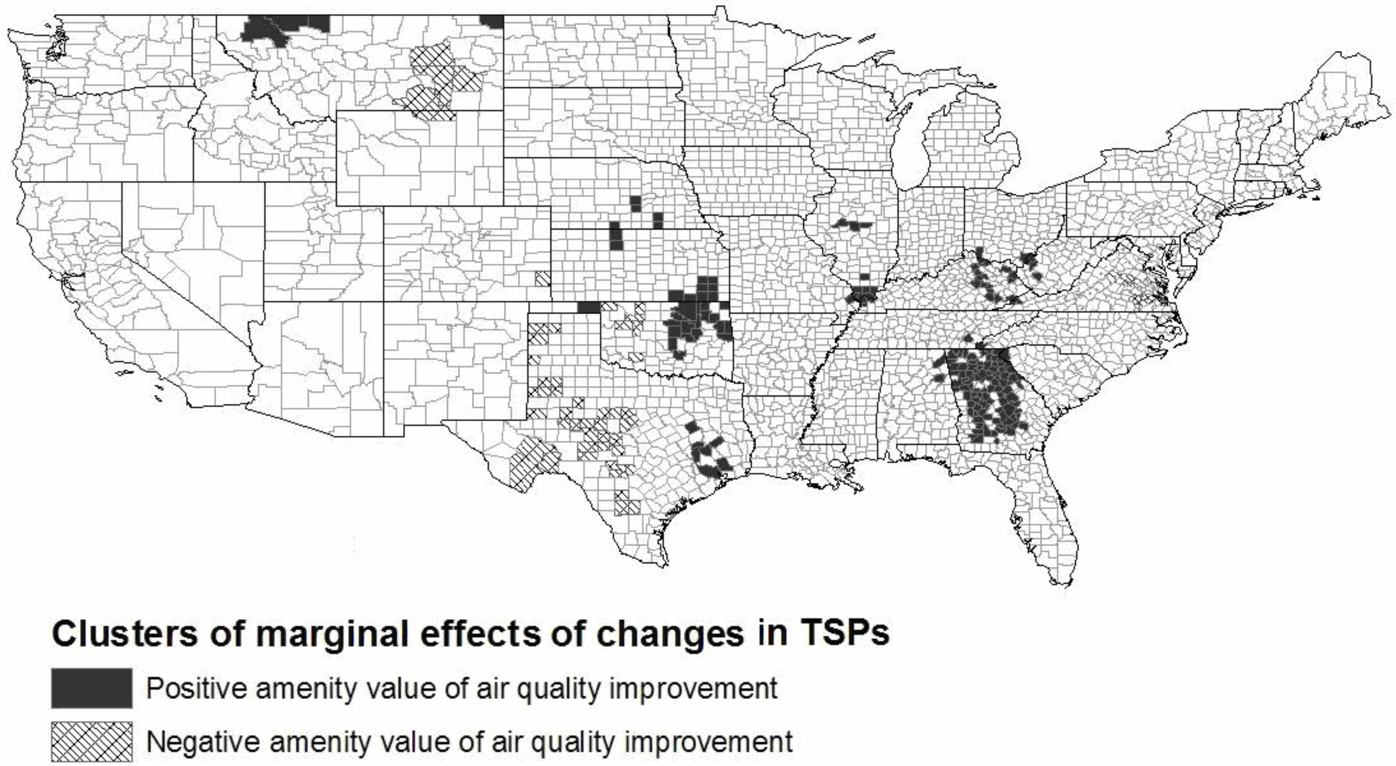


Figure 4. Clusters of marginal effects of changes in TSPs between 1990 and 2000

Vita

Seung Gyu Kim was born in Incheon, Korea on March 14, 1977. He entered Korea University and in February 2003 received the degree of Bachelor of Economics, *summa cum laude* and early graduation. In the fall of 2005 he began the Master of Science program in Agriculture Economics at the University of Tennessee, Knoxville and in the summer of 2007 graduated with the Agriculture Economics Master of Science degree.