8-2011

Essays in Spatial Analysis of Land Development and Recreation Demand

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To the Graduate Council:

I am submitting herewith a dissertation written by Seung Gyu Kim entitled "Essays in Spatial Analysis of Land Development and Recreation Demand." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Natural Resources.

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Essays in Spatial Analysis of Land Development and Recreation Demand

A Dissertation
Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Seung Gyu Kim
August 2011

DEDICATION

This dissertation is dedicated to my wife, Jieun.

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my advisor, Dr. Seong-Hoon Cho, for guiding this research and serving as a mentor throughout my graduate studies. I learned a lot from his research which were generously shared with me. His experience and scholarly advice were essential during the whole process of the dissertation and made its completion possible. More importantly, he helped me channel my enthusiasm toward the production of a well-defined scholarly product. Not only I deeply appreciate him as a scholar but I also thank him an earnest friend of mine. His extraordinary attitude toward his life including the economic research was one of his virtues I would like to pursue with my full respect.

I also would like to express my appreciation to my other committee members, Dr. Roland Roberts, Dr. Dayton Lambert, and Dr. Donald Hodges. I am indebted to Dr. Roberts who along with Dr. Cho played a critical role in mentoring and guiding me throughout my graduate program. My thanks go to Dr. Lambert who introduced me to spatial econometrics in depth which I am challenging and struggling with as life-time homework for my future academic career. My thanks also go to Dr. Donald Hodges who provided me continuous support and encouragement throughout my graduate study at The University of Tennessee. I also wish to thank Ms. Mary Gage for providing secretarial support in the most cheerful manner. Finally, thanks are in order for the Department of Agricultural and Resource Economics at the University of Tennessee for providing me with the necessary resources to complete my Doctorate Program.

ABSTRACT

This dissertation considers three topics under the themes of wetland restoration, urban sprawl, and recreation demand employing spatial data and analysis. A key question addressed in the first essay is how we can identify priority areas for wetlands restoration along the Louisiana coast under the Coastal Wetlands Planning, Protection, and Restoration Act by estimating amenity values received by nearby residents from hypothetical wetlands restoration projects. The second essay evaluates the effectiveness of alternative land-use policy variables for controlling development in a sprawling metropolitan area during two extreme market conditions. The third essay estimates the effect on consumer welfare from improved satisfaction of recreation information availability.

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INTRODUCTION

This dissertation considered three topics under the themes of wetland restoration, urban sprawl, and recreation demand employing spatial data and analysis. A key question addressed in the first essay was how we can identify priority areas for wetlands restoration along the Louisiana coast under the Coastal Wetlands Planning, Protection, and Restoration Act by estimating amenity values received by nearby residents from hypothetical wetlands restoration projects. A sequence of hedonic models across ranges of census-block groups was used to estimate differences in amenity values between existing wetlands and open water (wetlands lost to open water) areas. The differences between amenity values for wetlands and open water were used to estimate the value added to houses resulting from a given wetlands restoration project at a potential target site under the assumption that the opportunity cost of open water is recoverable with wetlands restoration. The prioritization of the potential target sites based on the aggregate values estimated in this study (non-use amenity values received by local residents) can contribute to the process of ranking areas for wetlands restoration for funding decisions under the Coastal Wetlands Planning, Protection, and Restoration Act as a complement to the current priority assessment focused solely on the use value of the biological habitat.

The second essay was designed to evaluate the effectiveness of alternative land-use policy variables for controlling development in a sprawling metropolitan area during two extreme market conditions. Specifically, two hypotheses were tested: (1) the alternative sprawl-management policies promote more compact and less leapfrogging development and (2) the effectiveness of the policies in controlling sprawl varies between the boom and recession periods. In sum, a property tax on land value promoted more compact and less leapfrogging development during the boom, zoning of land for agricultural use was an effective tool for mitigating residential development in general during the boom and recession but did not encourage more compact and less leapfrogging development during either period, and an Urban Growth Boundary (UGB) did not affect development nor the spatial pattern of development during the boom or the recession.

The third essay estimated the change in consumer welfare due to higher satisfaction of recreation information availability using on-site sample data collected from the Allegheny National Forest. The marginal effect of satisfaction of recreation information availability on the number of visits to the site was positive and significant. *Ex ante* simulation showed that individual annual per capital consumer welfare was increased when perfectly satisfied recreation information availability was assumed hypothetically. Thus, under the assumption that providing quality information about recreational activities increases visitor satisfaction, quality recreational information promotes higher social welfare among visitors. The results can be useful for budget decisions with regard to the providing of quality recreation information.

CHAPTER I

IDENTIFYING PRIORITY AREAS FOR WETLANDS RESTORATION ALONG THE LOUISIANA COAST UNDER THE COASTAL WETLANDS PLANNING, PROTECTION, AND RESTORATION ACT OF 1990

A version of this chapter was originally published by Seung Gyu Kim, Seong-Hoon Cho and Roland K. Roberts:

Seung Gyu Kim, Seong-Hoon Cho, Roland K. Roberts. “Identifying Priority Areas for Wetlands Restoration along the Louisiana Coast under the Coastal Wetlands Planning, Protection, and Restoration Act of 1990.” *Canadian Journal of Agricultural Economics 59* (2011): 295-320.

Seung Gyu Kim initially presented, “Prioritizing Wetland Restoration Decisions in the Delta States,” at the International Workshop on Wetlands Management, Economics and Policy in Victoria, BC, Canada. Through close co-working with Dr. Cho and Dr. Roberts, the manuscript was developed to publishable quality.

Abstract

This research used a sequence of hedonic spatial regressions across successively larger ranges of contiguous census-block groups (CBGs) to identify priority areas for wetlands restoration along the Louisiana coast under the Coastal Wetlands Planning, Protection, and Restoration Act (CWPPRA). Marginal implicit prices of wetlands and open water from the regressions were translated into amenity values received by single-family house owners within five Queen orders of CBGs. Differences between amenity values of wetlands and open water were used to proxy the amenity values of four potential restoration sites. These differences were summed over housing locations within each order of contiguous GBG neighbors and across the orders for each site. Based on the aggregate amenity value per acre from wetlands restoration and under the assumption that

most restoration projects are designed to benefit as wide an area as possible, the priority ranking for restoration becomes: 1) Fresh Bayou, 2) Sabine National Wildlife Refuge, 3) Bayou LaBranchee, and 4) Barataria Bay Waterway.

Introduction

Coastal wetlands loss in Louisiana is a continuing concern because of the essential roles that wetlands perform (e.g., ecological functions that benefit people and the ecological systems surrounding the wetlands) (Walker et al. 1987). Louisiana is estimated to have lost more than 1.2 million acres of coastal wetlands during the 20th century (CWPPRA 2006). If the current rate continues, Louisiana's delta plain is expected to lose an additional 431,000 acres of wetlands by 2050 (Barras 2003). The massive loss of Louisiana wetlands can be traced to a combination of natural causes and human activity (Porter and van Kooten 1993). The primary human-induced cause of wetlands loss is the construction of flood-control levees along the Mississippi River. Levees prevent wetlands from receiving much of the fresh water and nutrients necessary to their survival (Boesch 1994). Canals and navigation channels dredged through the marsh have also contributed to the loss of wetlands (U.S. Environmental Protection Agency 2007). Natural causes of wetlands loss include hurricanes, sea level rise, land subsidence, and excessive marsh loss due to nutria feeding activity (Office of Coastal

Protection and Restoration 2010).[1] For example, Louisiana lost 138,880 acres of coastal wetlands to open water immediately after Hurricanes Katrina and Rita (Zellmer 2007).

Government agencies have responded to concerns over the loss of wetlands and their associated ecosystem services by implementing a variety of policies and programs designed to reduce wetlands loss and promote their restoration. An example of the government's efforts is the Coastal Wetlands Planning, Protection, and Restoration Act (CWPPRA) of 1990. The CWPPRA funds wetlands enhancement projects nationwide, designating approximately $60 million annually for work in Louisiana through the Louisiana Coastal Wetlands Program. Since the start of the program in 1990, 145 projects have been developed or approved for development under the CWPPRA, benefiting over 110,000 acres of land. Over 70,000 acres of land are expected to be protected so that destroyable wetlands are reestablished to sites where they existed and an additional 320,000 acres enhanced by improving a particular function or value of wetlands (e.g., habitat for targeted species and recreational and educational opportunities) over the 20-year duration given to each project (La Coast 2010). The CWPPRA requires identification of eligible coastal wetlands projects that can be completed within a 5-year period along with the development of a long-term wetlands restoration plan (La Coast 2010). The task force sets forth provisions concerning the eligibility criteria for collaborative wetlands restoration proposals for the long-term conservation of wetlands and the dependent fish and wildlife populations. Other eligible criteria include technical

[1] The nutria is a South American rodent resembling a small beaver (WordNet 2010).

feasibility and an allowance for small-scale projects necessary to demonstrate the use of new techniques or materials for coastal wetlands restoration (Louisiana Coastal Wetlands Conservation and Restoration Task Force 1997).

Once projects are vetted for eligibility, all projects are scored, ranked, and prioritized through a voting process among the State of Louisiana, the counties in Louisiana, and 5 federal agencies (i.e., the U.S. Army Corps of Engineers, the U.S. Department of Agriculture, the U.S. Department of Commerce, the U.S. Department of the Interior, and the U.S. Environmental Protection Agency) based on an assessment prepared by the technical committee, which focuses on the biological habitat. A good example of the assessment is the Wetland Value Assessment Methodology (WVA) developed by the U.S. Fish and Wildlife Service (Environmental Work Group 2006). The WVA is used to compare wetlands of different types in terms of the average annual habitat units of resting, foraging, breeding, and nursery habitat for a diverse assemblage of fish and wildlife species (i.e., the total number of fish and wildlife habitat units gained or lost as a result of a proposed action divided by the life of the action) and the cost per average annual habitat unit for all projects (Miller and Gunsalus 1997). Thus far, however, other non-use values such as amenity values of wetlands restoration for nearby residents (e.g., open space, enhanced views, increased wildlife, and a buffer against noise and other forms of pollution) have not entered into the assessment.

The objective of this study is to contribute to the process of identifying priority areas for wetlands restoration along the Louisiana coast under the CWPPRA by estimating amenity values received by nearby residents from hypothetical wetlands restoration projects. A number of researchers have used the hedonic price method to investigate the amenity values of wetlands received by nearby residents (e.g., Bin and Polasky 2002; Doss and Taff 1996; Mahan, Polasky and Adams 2000). However, the values of hypothetical wetlands restoration projects are not estimable directly using a single hedonic model because the hedonic model uses measures of surrounding housing locations at the time of sales transactions, measures that would change after restoration. Instead, a single hedonic model captures the average values of both existing wetlands (hereafter referred to as “wetlands”) and prior wetlands that were lost to open water (hereafter referred to as “open water”). The difference between these two values from a single hedonic model can be considered as an average value of wetlands restoration in any given location under the assumption that the value of the foregone benefit due to the wetlands loss to open water can be restored to local residential real estate markets.

Such an average value of wetlands restoration does not constitute assessment information that is directly helpful for project prioritization under the CWPPRA. The information is not helpful because once eligible projects are chosen, the critical question for prioritization is the total amount of amenity value that will be received for a given restoration project at a particular location, not the amount of average amenity value that can be recovered from wetlands restoration at any given location. A four-step procedure developed by Cho et al. (2010) is employed to estimate the total amenity value for a particular restoration project at a particular location.

Under the four-step procedure, differences between amenity values of wetlands and open water for median housing values are estimated for census block-groups (CBGs) based on a sequence of repeated hedonic regressions across successive Queen orders of contiguous CBG neighbors (see the details of how the series of such regressions is estimated in the "Methods and Empirical Model" section).[2] Unlike a single hedonic model, the sequence of repeated hedonic regressions provides a series of amenity values for wetlands and open water areas for each order of contiguous neighbors. It is expected that the amenity values of the respective areas decrease as measures of the areas expand from lower- to higher-order neighbors. This series of values is used to estimate different levels of restorable benefits over different orders of neighbors, given a restoration project at a particular location. Moreover, analysis using readily available CBG data allows decision makers to assess restorable benefits relatively quickly and inexpensively compared to the four-step hedonic procedure in Cho et al. (2010) that uses parcel-level data.

Study Area and Data

This research employs three datasets in a geographical information system (GIS): satellite imagery data, CBG data, and environmental feature data. The study area covers 1,769 CBGs within the coastal watersheds of the State of Louisiana (lightly shaded areas in Figure 1). The mean CBG area is 21.26 square kilometers with a standard deviation of

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[2] A CBG is a cluster of census blocks. CBGs generally contain between 600 and 3,000 persons, with an optimum size of 1,500 individuals. The population in each CBG is the aggregate of a cluster of census blocks. The Census Bureau collects data every ten years based on a sample survey of roughly one in every six households, generally on April 1 in years ending in zero (U.S. Census Bureau 2000). Data are released by various jurisdictional boundaries and smaller boundaries of census blocks, CBGs, and census tracts.

73.45 square kilometers. Wetlands data were estimated based on classified U.S. National Land Cover Data (NLCD) derived from Landsat 7 imagery for 2001 (National land cover data 2001). The NLCD has 21 different land cover classifications at a resolution of 30 meters (National land cover data 2001). Of the 21 classified land covers, the areas classified as 'woody wetlands' and 'emergent herbaceous wetlands' were aggregated to construct the series of wetlands-area variables for different Queen orders of contiguous CBG neighbors. To measure the areas lost to encroachment of open water or agricultural land, GIS area raster files of NLCD 1992-2001 Retrofit Change Product were used (National land cover data 2008). Of the 63 land-cover-change classifications between 1992 and 2001, the areas classified as "wetlands to open water" and "wetlands to agriculture" were used to construct a series of wetlands-loss variables for the different orders of contiguous CBG neighbors. The U.S. Census schedule does not allow a perfect match between census and land classification records. Nevertheless, the land cover classifications from NLCD 2001 and land cover change classifications from NLCD 1992-2001 were assumed to be representative of the CBG data from the 2000 Census (U.S. Census Bureau 2000).

The median value of owner-occupied houses used in this study was the median value from U.S. Census estimates of the sale prices of census respondents' properties (houses and lots) as if the properties were for sale at the time of the survey. The value included single-family houses on less than 10 acres without a business or medical office on the property (U.S. Census Bureau 2000). Structural characteristics available from the census (i.e., median number of rooms, percentage of houses with complete kitchen, percentage of houses with complete plumbing, median age of houses, percentage of houses with gas or electricity heating, percentage of mobile homes, and housing density) were used as structural variables in the hedonic models. Percentages of houses with a complete kitchen, complete plumbing, and gas or electric heating were in the high 90s (99.6%, 98.41%, and 99.23%) with fairly low standard deviations (1.48, 2.91, and 1.79). Nonetheless, these variables were included in the hedonic models to explain a few outliers.

Socioeconomic variables from the census were reflected by mean per capita income, travel time to work, vacancy rate, unemployment rate, percentage of population with some college education, percentage of senior citizens, and percentage of houses continuously occupied for 5 years or more. These variables were included as measures of the relative socioeconomic status of a neighborhood. Locational variables included distances to the nearest metropolitan statistical area (MSA, a geographical region with a relatively high population density at its core and close economic ties throughout the United States), interstate highway, national park/forest, state park/forest, local park/forest, lake/reservoir, beach, and Louisiana coast. These distance variables were intended to capture the effects of proximities to various amenities and disamenities on the median value of houses. Other locational variables employed were elevation and dummy variables for rural-urban interface, adjacency to the Mississippi River, and floodplain zone. The elevation, adjacency to the Mississippi River, and floodplain zone variables were used to represent geological characteristics and the rural-urban interface was used to capture the effect of suburban development patterns.

ArcMap and ArcView GIS software (Environmental Systems Research Institute 2000) were employed to generate the distance and elevation variables. Distance and elevation calculations were made using a raster system where all data were arranged in grid cells. Distances were measured as the Euclidean distance from the centroid of a CBG to the centroid or the line of a feature. Elevation data were from the U.S. Geological Survey National Elevation Dataset (NED) (U.S. Geological Survey 2001). The NED had a resolution of one arc-second or approximately 30 meters. Landscape Management System Analyst, an extension for ArcGIS, was used to calculate average elevation by CBG (Rural Technology Initiative 2005). Detailed definitions and descriptions of the variables, including identification of the instrumental variables, are presented in Table 1.[3]

Methods and Empirical Model

A four-step procedure for prioritizing projects under the CWPPRA

A sequence hedonic spatial regressions, with median housing values at the Census Block Group level as the dependent variable, was used to generate implicit price estimates for wetlands and open water (prior wetlands lost to open water) areas. The first

[3] It is true that the mean values of both wetland loss variables are small; however, these small mean values have relatively large variations (with standard deviations greater than the mean values) across the six models. Without variation in the independent variable, all the observations would lie on a vertical line (Greene 1993, p.266). If the coefficient of variation (CV) for an independent variable (= standard deviation / mean) > 1, the variable is considered high-variance, while the variable is considered low variance if CV < 1. In our case, the CVs of both wetland loss variables are greater than 1; thus, we can safely say that the small means are not problematic in the estimation of our hedonic models because each has sufficient variation.

step entails estimating a series of such areas by constructing different orders of Queen contiguity weigh matrixes W based on CBG boundaries (e.g., own-, first-, and second-order Queen contiguity weight matrix). [4] In this case, conceptually, a CBG is assumed to be a representative 'property' for the houses within the CBG. Thus, constructing the spatial weight matrix based on CBG boundaries may fail to capture the spatial heterogeneity within CBGs. However, spatial heterogeneity should not be a major concern because CBGs are specified based on relative homogeneity in community characteristics such as population attributes, environmental living conditions, and economic status (including the housing market), and thus spatial heterogeneity within CBGs should not be substantial (U.S. Census Bureau 2000). Goodman (1977) examined a set of data with different aggregation levels and concluded that CBG-level data appear to be particularly useful for both descriptive and analytical uses such as hedonic price modeling. Shultz and King (2001) concluded that CBG-level aggregation is preferable to block- or tract-level aggregation in the application of a hedonic price model. In addition, general moment (GM) procedures (described in the "Methods and Empirical Model") mitigate the potential problem caused by unknown heteroskedasticity in the spatially autoregressive disturbance process (Kelejian and Prucha 2004). As a result, the use of CBG-level data does not substantially reduce the amount of variation in the amenity value of wetlands or open water, and thus the potential bias generated by within-CBG

[4] While Rook contiguity is measured based on a shared border and Bishop contiguity is measured based on a shared vertex, Queen contiguity incorporates both Rook and Bishop relationships into a single measure.

spatial heterogeneity of the amenity values of wetlands or open water should not be significant.

The own-order Queen contiguity weight matrix was structured so that the diagonal elements of the spatial weight matrix w_{ij} have a value of 1 and the off-diagonal elements have a value of 0. The first-order Queen contiguity weight matrix was structured so that if the *i*th and *j*th CBGs share a common geographic border or vertex, the off-diagonal elements of the spatial weight matrix w_{ij} have a value of 1 and 0 otherwise, and the diagonal elements of W have a value of 0. The second-order Queen contiguity weight matrix was structured so that if the *i*th and *j*th CBGs share a common geographic border or vertex or if the *i*th and *j*th CBGs have a common neighbor with which they directly share a border or a vertex, the off-diagonal elements of the spatial weight matrix w_{ij} have a value of 1 and 0 otherwise, and the diagonal elements of W have a value of 0. The third-, fourth-, and fifth-order Queen contiguity weight matrices were constructed following the same logic of sequences.

By multiplying each successive order of spatial weight matrix by the vectors of wetlands and open water areas at the CBG level, wetlands and open water areas for the different orders of contiguous neighbors were measured as illustrated by the example in figure 2 for a particular CBG. In the example, the wetlands and open water areas for a own Queen contiguity weight matrix are based on the areas within the particular CBG ("own CBG"). Using a first-order Queen contiguity weight matrix, these areas are measured within the particular CBG and within the seven CBGs that surround it ("first-order neighbors"). The respective areas using a second-order Queen contiguity weight matrix are measured within the paticular CBG, the seven CBGs that surround it, and the eight CBGs that surround the seven CBGs ("second-order neighbors").

In the second step, the hedonic model for CBG median housing price was estimated six times (for the own- to fifth-order neighbors), each time replacing the areas of wetlands and open water with their respective areas within the next higher order of neighbors.[5] Wetlands area lost to agricultural land (hereafter referred to as "agricultural land") was also replaced in the six hedonic price models. All other variables were held constant across the models.

In the third step, the regression coefficients for wetlands and open water areas from each of the six regressions were used to calculate the respective marginal implicit prices. For example, using the mean of the median CBG value of owner-occupied houses ($89,501) and the coefficient for wetlands area from the own CBG regression (0.026×10^{-3}), the average marginal implicit price of wetlands per acre for the own CBG is $ 89,501 $\times$ (0.033×10^{-3}) = $2.95/acre. This marginal implicit price suggests that a one acre increase in wetlands area within own CBG increases the mean of the median CBG housing value by $2.95, *ceteris paribus*.

The final step in the project-prioritization process entails estimating the amenity values of restoring wetlands at potential target sites under the CWPPRA. Four eligible

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[5] Adding the areas-of-wetlands variables for each order of neighbors as explanatory variables in one hedonic equation may be an alternative approach. However, considering the high degree of correlation between the wetlands variables (0.44 – 0.76 for wetlands, 0.26 – 0.97 for wetlands loss to agricultural land, and 0.64 – 0.94 for open water), serious multicollinearity was anticipated. Thus, repeated hedonic regressions using the wetlands and wetlands loss variables for different orders of neighbors were estimated to obviate the multicollinearity issue.

coastal wetlands projects under funding consideration by the CWPPRA were chosen as target areas to represent wetlands lost to encroachment of open water (see Figure 1). The potential projects were prioritized by summing the differences between the marginal implicit prices of wetlands and open water for houses within each Queen order of contiguous CBG neighbors and across the six orders of neighbors for each potential restoration site. This procedure prioritizes potential restoration sites for action under the CWPPRA in a way that complements the biological habitat assessment prepared by the technical committee.

Hedonic model specification

The estimation of the hedonic models in the second step of the four-step procedure raises two econometric issues that need to be addressed. The first issue is the potential endogeneity of the wetlands-area variable. Because the extensive loss of Louisiana wetlands can be traced to a combination of natural causes and human activity, wetlands area may be co-determined with housing value. To address this issue, the hedonic model was first estimated with ordinary least squares (OLS). Endogeneity of the wetlands-area variable was then evaluated with the Durbin-Wu-Hausman test (Wooldridge 2003, pp. 483). This test revealed endogeneity in each of the six regressions since the null hypothesis of exogeneity of the wetlands variables was rejected at the 1% significance level (F-statistics of 3.1, 4.4, 4.9, 5.3, 5.3, and 5.2 and all p-values < 0.01). Thus, the instrumental variables (IV) approach was used to correct for the endogeneity (Maddala 1983; Irwin and Bockstael 2001; Cho, Poudyal and Roberts 2008; Cho et al.

2009). Land areas within CBGs was used as a unique instrumental variable for existing wetlands areas within CBGs. The instrument was chosen because the area of existing wetlands is correlated with CBG size (correlation coefficient of 0.94) but not with the disturbance term in the hedonic equation. The null hypothesis that the instrument was weakly identified was strongly rejected at the 1% level based on the Cragg-Donald Wald F-statistic (385.03) (Stock and Yogo 2005).

The second econometric issue in the hedonic price model is that housing prices at a given location are simultaneously determined by neighboring housing prices (Kim, Phipps and Anselin 2003; Anselin and Lozano-Gracia 2009). While there are numerous reasons why error terms in the hedonic price model may be spatially autocorrelated, the key reason is that nearby houses share common characteristics and hence, exhibit high dependence among the error terms. Spatial dependence can occur due to spatial correlation among house prices and as a consequence of spatial correlation in the errors. The data used in the hedonic price model are spatial in nature because they are based on house sales in a given area or location (Mueller and Loomis 2008). Thus, the price of a house is strongly influenced by the price and quality of houses immediately surrounding it, neighborhood quality, and its relative location to amenities (e.g., wetlands) and disamenities (e.g., point-source pollutant sites).

While many past studies attempted to control for neighborhood effects using census-tract demographics, school quality and distance to amenities, advances in spatial econometrics have facilitated the control of spatial dependence among house sales (spatial lag) and spatial correlation (spatially correlated errors) between the sales prices of houses and the errors (Anselin and Lozano-Gracia 2009). Such studies typically use a spatial process model, which includes explanatory variables; endogenous variable that accounts for spatial interactions between prices observed at transaction points; exogenous variables relating house attributes as well as geographic and demographic data; and a disturbance term. The interactions are modeled as a weighted average of nearby sales transactions. The endogenous variable accounting for the interactions is usually referred to as a spatially lagged variable. A relational matrix identifies connectivity between transactions, which differentiates hedonic spatial process models from other hedonic regression methods. Anselin and Florax (1995) call this model a spatial autoregressive lag model of the first order (SAR[1]).

The general hedonic price model contains a spatially lagged endogenous variable as well as spatially autoregressive disturbances in addition to exogenous variables, called a spatial autoregressive model with autoregressive (AR) disturbance of order (1,1) (SARAR) (Anselin and Florax 1995); $P = \rho W_1 P + X\beta + \varepsilon$, $\varepsilon = \lambda W_2 \varepsilon + u$, $u \sim iid(0, \Omega)$, where P is a vector of the natural logarithm of median value of owner-occupied houses in a CBG; X is a matrix of variables hypothesized to explain P including areas of wetlands and wetlands loss, β is a vector of their corresponding coefficients, ε is an error term, and W_1 and W_2 are (possibly identical) matrices defining interrelationships between spatial units. W_1P and $W_2\varepsilon$ capture spatially lagged terms for the dependent variable and error terms, respectively, and ρ and λ are corresponding parameters. In our study, the first-order Queen contiguity weight matrix W, that was row standardized such that the column sum of each row is one, was used to estimate the six hedonic models for own- to fifth-order neighbors.(Florax and Rey 1995; Le Gallo and Ertur 2003; Cotteleer, Stobbe and Van Kooten 2010)[6, 7]

When the W matrix is asymmetrical, the model is heteroskedastic (Anselin 2003), and $E[uu'] = \Omega$. The reduced form of the system makes clear how observations are globally correlated: $y = (I - \rho W_1)^{-1}X\beta + (I - \rho W_1)^{-1}(I - \lambda W_2)^{-1}u$, with $(I - \rho W_1)$ and $(I - \lambda W_2)$ as the lag and error filters. Even when W is a sparse matrix with most off-diagonal elements zero, the "Leontief" inverses of the filters are full matrices that amplify shocks between cross-sectional units. Full information maximum likelihood (FIML) (Anselin 1988) or general moment (GM) procedures (Kelejian and Prucha 2004; Anselin and Lozano-Gracia 2009) are typically used to estimate spatial process models in hedonic price studies. The GM procedure has several advantages over the FIML. First, the distributional assumption of normality is relaxed. Second, the GM procedure bypasses calculation of an *n* by *n* matrix determinant, which may be cumbersome with larger data sets. Thus, the six equations of the second IV stage were estimated as spatial models using Kelejian and Prucha's (2004) GM procedure.

[6] In general, there is no consensus as to which spatial weights are most appropriate for any econometric study (Anselin 1988), and the selection of appropriate weight matrices remains a challenge to practitioners (Le Gallo and Ertur 2003). Florax and Rey (1995) discuss some problems that may arise if spatial weights matrices are poorly selected. Cotteleer et al. (2011) employed Bayesian Markov Chain, Monte Carlo method to determine the appropriate weighting matrices in the application of a spatial hedonic pricing model. The main assumption is that the spatial weights matrix expresses the potential for interaction between observations at each pair *i*,*j* of locations

[7] For the estimating spatial lag parameter, Z=[X, WX, WWX] was used as instrumental variables. *J statistics* was 308.935, 299.341, 299.334, 299.698, 299.945, 297.200, and 294.501 for each regression, which rejected null hypothesis of E[Z|u]=0.

Empirical Results

The results of the first stage IV estimates for the six wetlands-loss equations are presented in Appendix Table A. The adjusted R^2s range from 0.65 to 0.91. Consistently significant coefficients for the spatial lag (ρ) and spatial error (λ) variables in the second stage IV spatial models confirm that spatial dependence is captured by the hedonic model through the spatial process (Table 2). [8]

Control variables in the second stage estimates

The results from the second stage IV regressions of the six spatial models are presented in Table 2. With a few noted exceptions, the discussion below is limited to coefficients that are significant at the 5% level. All significant coefficients among control variables behave as expected. Among the structural variables, the median number of rooms, median age of houses, percentage of mobile homes, and housing density are significant across the six regressions. More rooms, a younger age, a lower percentage of mobile homes, and more densely populated areas add value to houses. The added value of a lower percentage of mobile homes emphasizes the relationship between mobile homes and lower-income segments of society. Percentages of houses with a complete kitchen,

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[8] In an *ex post* analysis, the residuals were tested for spatial autocorrelation using the Queen contiguity weight matrix. The null hypothesis of no spatial dependence could not be rejected at any conventional level of significance. As another sensitivity analysis, an inverse distance matrix was used in each of the six regressions. The same conclusions were obtained: spatial dependence was significant across the regressions, while spatial lag was not. While it is difficult to conclude that the weight matrix used in this study is the best of all possible neighborhood specifications, the ex post LM error tests and the Wald tests of the regressions are encouraging in this respect.

plumbing, and gas or electric heating are not significant determinants of housing price, which may be because those structural features exist in almost all houses.

For the socioeconomic variables, the six models consistently show that a greater mean per capita income, lower unemployment rate, higher percentage of population with some college education, higher percentage of senior citizens, and higher percentage of houses continuously occupied for 5 years are associated with higher median house prices. Less travel time to work and a lower vacancy rate increased median house prices in some models. Among the locational variables, proximities to local parks/forests and beaches increased housing values as expected. The distances to a metropolitan statistical area (MSA), an interstate highway, and a national park/forest had expected negative signs, reflecting their positive amenity values, but were not always significant in all six regressions. Likewise, in five models, CBGs with rural-urban interface areas had greater housing values than those with no such areas.

Unexpectedly, proximities to a state park/forest, a lake/reservoir, and the Louisiana coast as well as elevation, and living adjacent to the Mississippi River or in floodplain zone are not significant in any of the six models. Proximity to the nearest Louisiana coast line as well as being adjacent to the Mississippi River were not significant, presumably because their natural amenities were offset by the disamenities of higher chances of flooding near the Louisiana coast and the Mississippi River. The insignificance of elevation could be explained by the premiums for views from higher elevations being offset by less convenient transportation. The insignificance of living in a floodplain zone could be explained the frequent and heavy flooding caused by hurricanes in Louisiana. Thus, the disamenity from living in a floodplain zone may be small compared with the amenities of not living in a floodplain, other things constant.

Existing wetlands and open water in second stage estimates

In all the six regressions, existing wetlands are valued positively while open water is not valued and wetlands areas that were lost to agricultural land are valued negatively for the third-to-fifth orders of CBG neighbors. Because the variables for open water are not significant across the different orders of neighbors, their marginal implicit prices are assumed to be zero. Since agricultural land is not considered for wetlands restoration under the CWPPRA, the opportunity cost of the areas lost from wetlands to agricultural land is considered unrecoverable. Thus, the marginal implicit prices of wetlands areas across different orders of CBG neighbors in Table 3 represent the differences in the values of wetlands and open water areas across different orders of neighbors. The marginal implicit price of wetlands area is at its peak ($2.95 per acre) for the own CBG and decreases gradually as the order of neighbor increases, holding other factors constant.

Figure 1 shows the location of the four eligible coastal wetlands projects as hypothetical target areas for wetlands restoration under funding consideration by the CWPPRA. Summing the added amenity values per acre of wetlands restoration for the houses within own- to fifth-order CBG neighbors for selected target sites gives the average amenity values per acre of wetlands restoration in Table 4. Because the marginal implicit price is higher for houses closer to a target restoration site, the value per acre of wetlands restoration is higher for closer CBG neighbors and those with more houses.

Based on the increased amenity value per acre from wetlands restoration within own- to second-order CBG neighbors, the priority ranking for the four target sites is mixed, with a different ranking for different CBG neighbors. The priority ranking converges to 1) Fresh Bayou, 2) Sabine National Wildlife Refuge, 3) Bayou LaBranchee, and 4) Barataria Bay Waterway based on the aggregated amenity value per acre within third- to fifth-order CBG neighbors. The priority is unlikely to be changed beyond the fifth-order neighbors given the low marginal implicit price per acre of wetlands within the fifth-order CBG neighbors ($0.26 per acre) and the consistently decreasing marginal implicit price of wetlands area with increasing orders of CBG neighbors. The priority ranking within the third- to fifth-order neighbors can be used as complementary information for guiding CWPPRA funding decisions to implement restoration projects designed to benefit as wide an area as possible.[9]

Conclusion

This research was motivated because the amenity values received by local residents have not been included among the eligibility criteria and prioritization factors used to make funding decisions about wetlands restoration under the CWPPRA. A sequence of hedonic models across ranges of CBGs was used to estimate differences in

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[9] Alternatively, measurement of marginal implicit price could be calculated based on direct/indirect/total marginal effects with their statistical significances, but we used only direct marginal effects and parameter significances for the convenience of aggregating the added values per acre of wetlands restoration. Since their indirect effects are same across the space, the ranking of aggregate added value using the alternative method stays the same as given in the manuscript.

amenity values between existing wetlands and open water (wetlands lost to open water) areas. The differences between amenity values for wetlands and open water were used to estimate the value added to houses resulting from a given wetlands restoration project at a potential target site under the assumption that the opportunity cost of open water is recoverable with wetlands restoration. The prioritization of the potential target sites based on the aggregate values estimated in this study (non-use amenity values received by local residents) can contribute to the process of ranking areas for wetlands restoration for funding decisions under the CWPPRA as a complement to the current priority assessment focused solely on the use value of the biological habitat.

Several caveats are important to mention. The first three caveats relate to data limitations. First, the differences in amenity values associated with existing wetlands and lost wetlands were estimated without accounting for variation in the quality of wetlands. Therefore, the marginal effects of wetlands on individual preferences are ultimately constrained to be similar across different attributes. For example, Mahan et al. (2000) find significant variation in amenity values on property prices depending on wetlands quality, including shape (e.g., linear or areal) and content (e.g., no vegetation, with emergent vegetation, with scrub-shrub). These variations in wetlands quality could not be included in the spatial hedonic model used in this study because the NLCD did not provide such detailed information. Second, the amenity values of wetlands estimated in this study do not capture the dynamics of the housing market (i.e., lags between changes in amenities and their influences on housing values) because the hedonic model is estimated as a snapshot of the median housing value found in the 2000 census (Freeman

1993; Smith and Huang 1995). If National Land Cover Data were available to match earlier or later census years, the dynamics of the housing market could be captured in the analysis. Third, more accurate estimation of the differences could be estimated using sales transactions data across a series of areas with increasing radii around the location of each sales transaction. As a future study, we may want to compare the differences in amenity values found in this study with the differences in amenity values based on each sale transaction and its surrounding areas.

The last caveat is associated with the limitation of hedonic model. While the hedonic model can be used to estimate amenity values received by nearby residents, it is important to remember that the method provides only a limited measure of total economic benefit. The amenity values may not be fully reflected in signal-housing prices. House prices also do not reflect benefits received by businesses, renters, and visitors. For these reasons, estimates from hedonic housing price models will generally underrepresent the true value of these amenities. In addition, this method only captures those values that are capitalized into the local residential housing market, and it is unclear how these values relate to the Wetland Value Assessment Methodology (WVA) and other biological-based attempts at quantifying benefits.

Table 1. Variable Names, Definition, and Identification of the Instrumental Variables

Variable	Definition	Mean	Std. Dev.
Dependent variable			
Median house price	Median value of owner-occupied houses (2000 dollars)	89,504.74	66,511.11
Variables of interest			
Wetlands (own CBG)	Areas classified as "woody wetlands" and "emergent herbaceous wetlands" (acre) based on NLCD (2001) within own CBG	263.24	13,36.69
Wetlands loss to open water (own CBG)	Area classified as 'wetlands to open water' (acre) based on NLCD (1992/2001) within own CBG	0.001	0.003
Wetlands loss to agricultural land (own CBG)	Area classified as 'wetlands to agricultural land' (acre) based on NLCD (1992/2001) within own CBG	0.001	0.004
Structural variables			
Median number of rooms	Median number of rooms per house	5.77	0.80
Percentage of houses with complete kitchen	Percentage of houses with complete kitchen (%)	99.60	1.48
Percentage of houses with complete plumbing	Percentage of houses with complete plumbing (%)	98.41	2.91
Median age of houses	Median age of houses (years)	35.55	14.64
Percentage of houses with gas or electricity heating	Percentage of houses with gas or electricity heating (%)	99.23	1.79
Percentage of mobile homes	Percentage of mobile homes (%)	9.40	13.77
Housing density	Housing density (number of total housing units of any type per km^2)	827.65	923.94

Table 1 Continued

Variable	Definition	Mean	Std. Dev.
Socioeconomic variables			
Mean per capita income	Mean per capita income (Year 2000 dollars)	17,152.99	9,456.77
Travel time to work	Mean travel time to work (minutes)	25.52	7.12
Vacancy rate	Percentage of houses that are vacant (ratio of vacant housing units to total housing units of any type, %)	9.84	8.96
Unemployment rate	Percentage of the labor force that is unemployed (ratio of unemployed to the labor force, age 16 or older, %)	8.19	7.19
Percentage of population with some college education	Percentage of the population over 25 years old with at least some college (%)	40.74	20.12
Percentage of senior citizens	Percentage of population 65 years or older (%)	12.70	6.80
Percentage of houses continuously occupied for 5 years	Percentage of houses occupied continuously for at least 5 years (%)	72.33	13.57
Locational variables			
Distance to Metropolitan Statistical Area (MSA)	Distance to the nearest Metropolitan Statistical Area, which is a geographical region with a relatively high population density at its core and close economic ties throughout the United States as defined by the U.S. Office of Management and Budget (mile)	14.54	10.88
Distance to interstate highway	Distance to the nearest interstate highway (mile)	8.08	11.17
Distance to national park/forest	Distance to the nearest national park/forest (mile)	70.80	22.33
Distance to state park/forest	Distance to the nearest state park/forest (mile)	14.42	11.93

Table 1 Continued

Variable	Definition	Mean	Std. Dev.
Distance to local park/forest	Distance to the nearest local park/forest (mile)	5.86	7.75
Distance to lake/reservoir	Distance to the nearest lake/reservoir (mile)	6.14	5.38
Distance to beach	Distance to the nearest beach (mile)	35.51	18.42
Distance to Louisiana coast	Distance to the nearest Louisiana coast line (mile)	20.38	22.55
Elevation	Mean elevation (feet)	72.10	131.84
Rural-urban interface	CBGs in rural-urban interface area (1 if in census-block group of mixed rural-urban housing, 0 otherwise)	0.16	0.37
Adjacency to Mississippi River	CBG is immediately adjacent to the Mississippi river (1 if yes, 0 otherwise)	0.05	0.23
Floodplain zone	CBG is in 500-year floodplain zone (1 if yes, 0 otherwise)	0.59	0.49
Land area†	CBG land area (acre)	5,255.39	18,151.77

† Instrumental variable used as a unique instrument in the first-stage wetlands-loss regression.

Table 2. Estimation Results of the Second Stage Spatial CBG Hedonic Models using the IV Approach

Variable	Own CBG	First-order neighbors	Second-order neighbors	Third-order neighbors	Fourth-order neighbors	Fifth-order neighbors
	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
Intercept	24.200*	22.531*	22.847*	22.380*	20.773*	17.721*
	(3.563)	(3.558)	(3.353)	(3.555)	(3.572)	(3.653)
Variables of interest						
Wetlands ($\times10^{-3}$)	0.033*	0.012*	0.007*	0.005*	0.003*	0.003*
	(0.005)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Wetlands loss (open water)	-1,937.547	-0.167	-0.124	-0.090	-0.059	-0.037
($\times10^{-6}$)	(2,142.600)	(0.132)	(0.064)	(0.047)	(0.037)	(0.034)
Wetlands loss (agriculture)	-772.198	0.387	-0.179	-0.433*	-0.608*	-0.799*
($\times10^{-6}$)	(2,132.654)	(0.326)	(0.174)	(0.132)	(0.133)	(0.148)
Structural variables						
Median number of rooms	0.186*	0.186*	0.185*	0.185*	0.185*	0.182*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Percentage of houses with	0.001	0.001	0.001	0.002	0.002	0.002
complete kitchen	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Percentage of houses with	0.196	0.200	0.237	0.232	0.253	0.286
complete plumbing	(0.233)	(0.234)	(0.234)	(0.234)	(0.234)	(0.235)
Median age of houses	-0.003*	-0.003*	-0.003*	-0.003*	-0.003*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Percentage of houses with gas	-0.025	-0.117	-0.016	0.054	0.075	0.113
or electric heating	(0.334)	(0.334)	(0.336)	(0.338)	(0.339)	(0.339)
Percentage of mobile homes	-0.566*	-0.613*	-0.654*	-0.697*	-0.738*	-0.776*
	(0.066)	(0.066)	(0.067)	(0.069)	(0.072)	(0.075)

Table 2 continued

Variable	Own CBG	First-order neighbors	Second-order neighbors	Third-order neighbors	Fourth-order neighbors	Fifth-order neighbors
	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
Housing density ($\times 10^{-2}$)	0.002*	0.002*	0.003*	0.003*	0.003*	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Socioeconomic variables						
Mean per capita income	0.002*	0.002*	0.002*	0.002*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Travel time to work	-0.002	-0.002*	-0.003*	-0.003*	-0.003*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Vacancy rate	-0.002*	-0.002*	-0.002	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment rate	-0.003*	-0.003*	-0.003*	-0.003*	-0.003*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Percentage of population with	0.006*	0.006*	0.006*	0.006*	0.006*	0.007*
some college education	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Percentage of senior citizens	0.002*	0.003*	0.003*	0.002*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Percentage of houses	-0.187*	-0.190*	-0.195*	-0.205*	-0.217*	-0.226*
continuously occupied for 5 years ($\times 10^{-2}$)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)
Locational variables						
Distance to metropolitan	-1.045	-1.795	-2.260*	-2.318*	-2.165	-1.489
statistical area	(0.991)	(0.014)	(1.061)	(1.101)	(1.130)	(1.173)

Table 2 continued

Variable	Own CBG	First-order neighbors	Second-order neighbors	Third-order neighbors	Fourth-order neighbors	Fifth-order neighbors
	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
Distance to interstate highway	-0.597	-0.649	-1.199	-2.561*	-4.879*	-8.131*
	(1.120)	(1.152)	(1.185)	(1.246)	(1.417)	(1.702)
Distance to national park/forest	-4.399*	-3.762*	-3.881*	-3.758*	-3.268*	-2.266
($\times 10^3$)	(0.236)	(0.235)	(0.235)	(0.235)	(0.236)	(0.240)
Distance to state park/forest	-0.064	-0.066	-0.048	-0.031	-0.053	-0.120
($\times 10^3$)	(0.071)	(0.071)	(0.071)	(0.071)	(0.072)	(0.073)
Distance to local park/forest	-0.061*	-0.079*	-0.091*	-0.098*	-0.099*	-0.095*
($\times 10^3$)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Distance to lake/reservoir	-1.885	-0.539	-0.216	-0.354	-0.665	-0.924
	(1.740	(1.747)	(1.776)	(1.767)	(1.755)	(1.739)
Distance to beach ($\times 10^3$)	-0.815*	-0.846*	-0.906*	-0.911*	-0.821*	-0.681*
	(0.032)	(0.032)	(0.033)	(0.033)	(0.033)	(0.033)
Distance to Louisiana coast	0.035	-0.005	-0.002	0.003	0.008	0.021
($\times 10^3$)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Elevation ($\times 10^{-2}$)	-0.116	-0.074	-0.059	-0.031	0.046	0.187
	(0.138)	(0.139)	(0.139)	(0.140)	(0.141)	(0.147)
Rural-urban interface	0.088*	0.085*	0.075*	0.063*	0.049*	0.034
	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)	(0.020)
Adjacency to Mississippi River	0.003	0.010	0.018	0.025	0.031	0.033
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.029)
Floodplain zone ($\times 10^{-1}$)	0.259	0.206	0.126	0.080	0.042	-0.001
	(0.135)	(0.136)	(0.138)	(0.139)	(0.141)	(0.143)

Table 2 continued

Variable	Own CBG	First-order neighbors	Second-order neighbors	Third-order neighbors	Fourth-order neighbors	Fifth-order neighbors
	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
Spatial lag	0.303*	0.343*	0.303*	0.301*	0.303*	0.198*
	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)
Spatial error	0.303*	0.304*	0.303*	0.301*	0.300*	0.298*
	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)

* Significant at the $\alpha = 0.05$ level (5%).

Table 3. Marginal Implicit Prices of Wetlands Area across Different Orders of CBG Neighbors

Neighbors of CBGs	Wetlands area ($\times 10^{-3}$) Coefficient (Std. Err.)	Wetlands area (acre)	Marginal Implicit price of wetlands area ($/acre)
Own CBG	0.033* (0.005)	263.24	2.95
First-order neighbors	0.012* (0.002)	1,865.04	1.07
Second-order neighbors	0.007* (0.001)	7,376.91	0.62
Third-order neighbors	0.005* (0.001)	19,385.27	0.44
Fourth-order neighbors	0.003* (0.001)	39,626.10	0.26
Fifth-order neighbors	0.003* (0.001)	70,970.63	0.26

* Significant at the $\alpha = 0.05$ level (5%).

Table 4. Sum of the Added Values per Acre of Wetlands Restoration to the Median Housing Value within Own- to Fifth-order CBG Neighbors

	Barataria Bay Waterway		Fresh Bayou		Bayou LaBranchee		Sabine National Wildlife Refuge	
	Number of houses	Aggregate added value ($/acre)	Number of houses	Aggregate added value ($/acre)	Number of houses	Aggregate added value ($/acre)	Number of houses	Aggregate added value ($/acre)
Own CBG	36	106	588	1,735	0	0	800	2,360
First-order neighbors	1,415	1,514	2,519	2,695	3,864	4,134	2,992	3,201
Second-order neighbors	4,499	2,789	7,226	4,480	9,769	6,057	12,680	7,862
Third-order neighbors	5,474	2,409	24,025	10,571	10,944	4,815	21,374	9,405
Fourth-order neighbors	7,750	2,015	43,363	11,274	15,833	4,117	27,907	7,256
Fifth-order neighbors	16,216	4,216	71,755	18,656	27,302	7,099	35,085	9,122

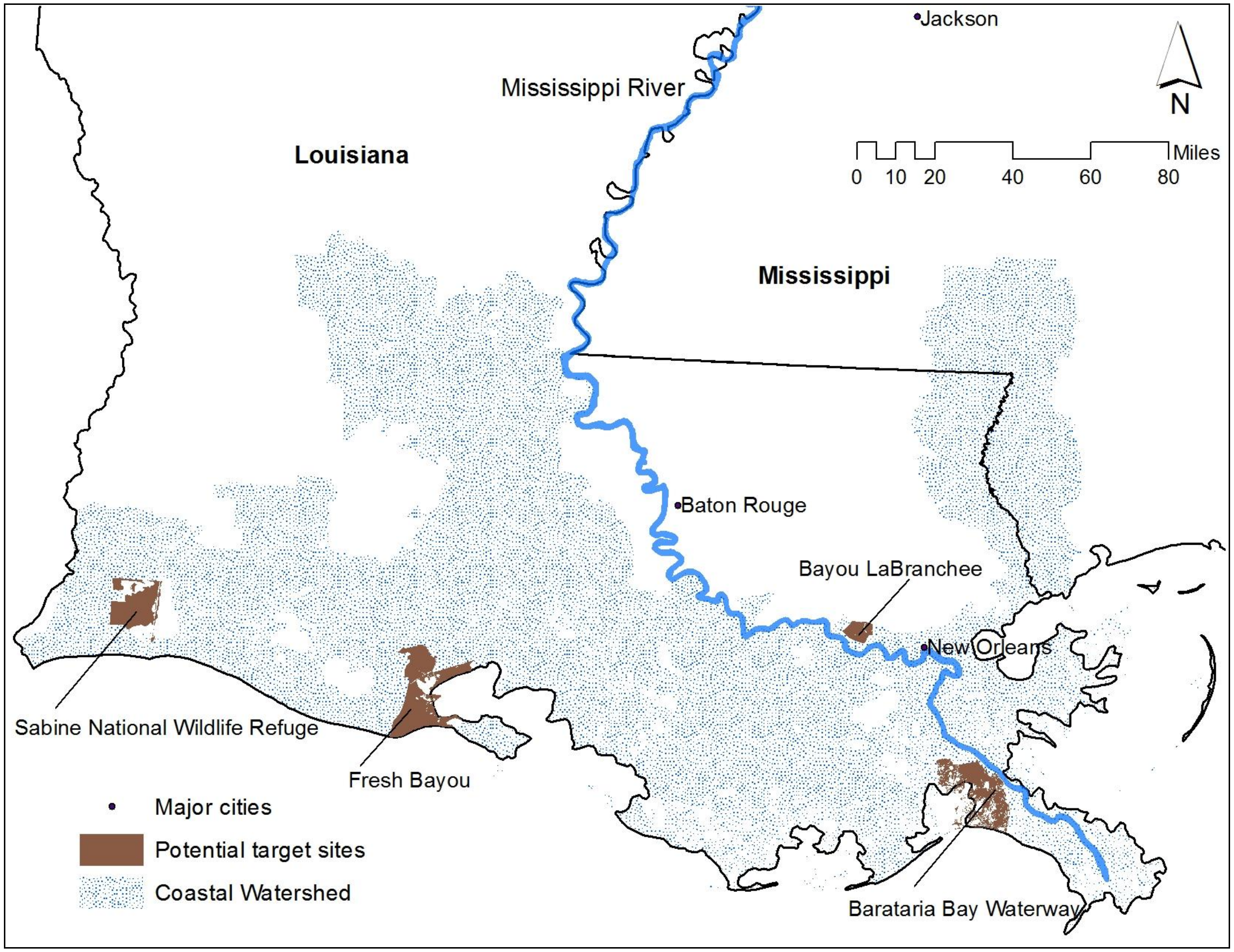

Figure 1. Four Eligible Coastal Wetlands Projects Chosen as Target Areas for Restoration of Wetlands under Funding Consideration by the CWPPRA

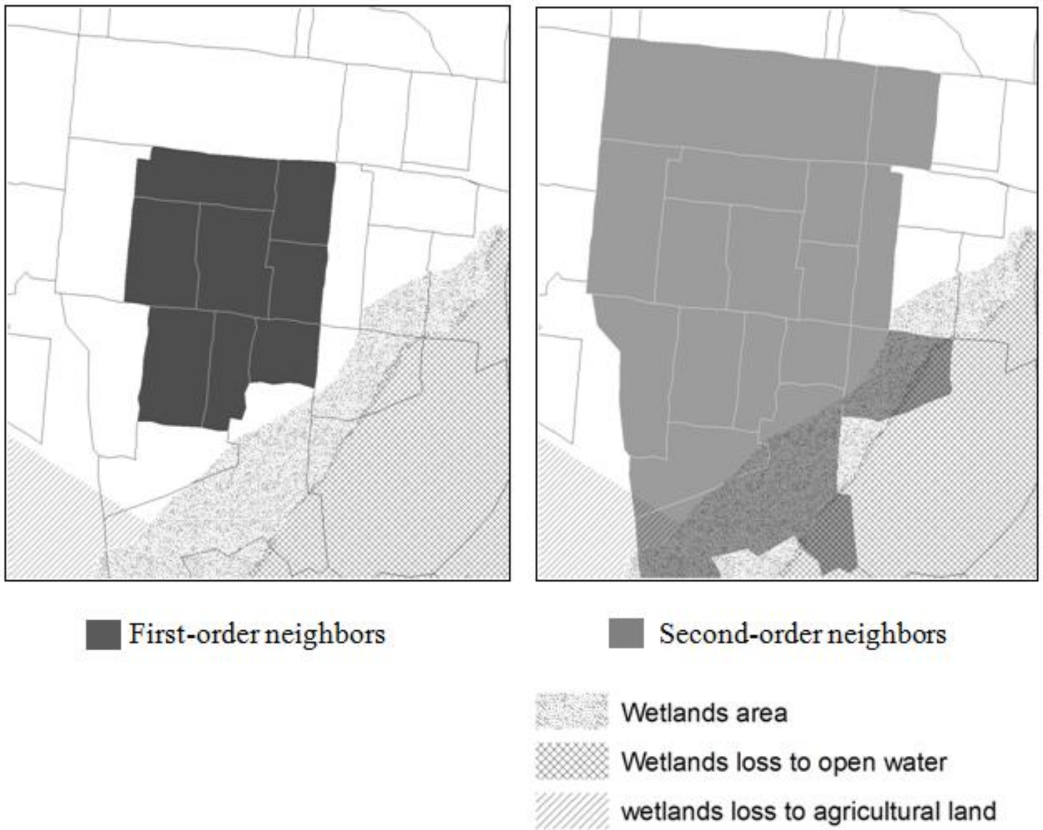

Figure 2. Wetlands and Wetlands Loss to Open Water and agricultural Land for the First- and Second-order Neighbors around the Location of a Sales Transaction

CHAPTER II

EFFECTIVENESS OF LAND-USE POLICY TOOLS FOR CONTROLLING SPRAWL DEVELOPMENT DURING A REAL ESTATE BOOM AND A RECESSION

Abstract

A parcel-level land conversion model was developed to compare landscape pattern metrics with and without three land-use policies during a real estate boom and a recession. Two hypotheses were tested: (1) the sprawl-management policies promote more compact and less leapfrogging development and (2) the effectiveness of the policies in controlling sprawl varies depending on economic conditions. The effectiveness of implementing a land-value property tax in controlling sprawl development during the recent real-estate boom and its lack of effectiveness during the subsequent recession reveals that the effects of land-use policies on individual development decisions vary according to market conditions.

Introduction

Since World War II, urban sprawl (i.e., the leapfrogging of development beyond a city's outer boundary into smaller rural settlements) has become a widespread phenomenon in the United States (Jackson 1985). Urban sprawl has been driven by household preferences for bigger houses, larger lots, lower land prices, less noise and pollution, lower crime, and higher-quality schools (Hanham and Spiker 2005). This pattern of development, dominant in the United States for over 50 years, was interrupted during the first decade of the twenty-first century by the housing-market collapse and high gasoline prices (Gillham and MacLean 2002). Some economists believe there exists significant evidence that sprawl has been waning since mid-2007 when the US housing market began experiencing a sub-prime mortgage market "meltdown" (Bowen 2009).

With the housing slump and financial crisis taking their toll on real estate markets almost everywhere in the United States, including housing markets that were characterized by suburban sprawl before the housing market collapse, the slowdown of sprawl development is not surprising.

Regardless of the contributing factors to the recent slowdown of sprawl, the unanswered question is whether this slowdown is a cyclical or long-term shift. Some researchers argue that economic recession could lead to the long-term eradication of sprawling development. The underlying premises behind the argument are, in part, anticipation of continuous high gasoline prices and gradually diminishing preferences for larger-lot houses (Nelder 2008; Karlenzig 2010; Urban Land Institute and PricewaterhouseCoopers 2010).

Current high gasoline prices and potentially higher prices in the future point to a direct economic burden on households, depending on distance from the place of residence to work. The average gasoline price rose from under $2 per gallon for regular unleaded in the boom years to over $4 per gallon by 2008 (U.S. Energy Information Administration 2010). It has stayed over $2 per gallon since 2008 and is projected to reach $4 per gallon again by mid-2011, mainly due to ongoing turmoil in the Middle East (U.S. Energy Information Administration 2010). High gasoline prices increase the burden of transportation costs on household expenses. By one estimate, Americans spend $1.25 billion less on consumer goods for each one-cent increase in the price of gasoline (La Monica 2009). The burden on consumers is reflected in changes in their consumption patterns. The national average of vehicle miles traveled decreased 3.6 percent between

2007 and 2008 (American Public Transportation Association 2009). Increased transportation costs are an even greater burden on outer suburban residents than city dwellers because of their greater average transportation expense (Center for Neighborhood Technology 2010). The extra burden on household budgets has forced home foreclosures in exurban areas and encouraged outer suburban residents to move into city centers (Karlenzig 2010). Thus, high gasoline prices now and in the future may reduce sprawling development in the long run.

Another potential explanation for the long-term slowdown in sprawl is diminishing preferences for bigger houses among younger generations. Trends indicate that these groups continue to migrate into urban core areas, because instead of bigger houses on larger lots in suburban areas (Urban Land Institute and PricewaterhouseCoopers 2010), they prefer living in urban infill housing, such as apartments or townhouses, which are closer to cultural and entertainment attractions, require less upkeep, have less road congestion, and are more economically efficient in terms of energy costs. Among these populations, young households without children are less interested in the better educational environments that may exist in suburban areas, reducing the demand for suburban living that drives urban sprawl (Urban Land Institute and PricewaterhouseCoopers 2010).

While arguments for a long-term slowdown in sprawl may seem convincing, contrasting arguments suggest that the current slowdown is a temporary phenomenon. From this perspective, the overwhelming consensus is that the market will rebound eventually as it did after previous recessions (e.g., rebounds after 1982, 1991, and 2001 recessions), because of the cyclical nature of the real estate market (National Bureau of Economic Research 2010). Accordingly, the recovery will lead to at least a limited rebound in urban sprawl. The current stability in demand for factors that drive sprawl serves as one indicator. Much hedonic literature has shown that more finished area, larger lots, less noise and pollution, and higher-quality schools add value to houses regardless of the study area or study period (e.g., Anderson and West 2006; Anselin and Lozano-Gracia 2009; Cavailhès et al. 2009; Cho et al. 2006, 2008, 2009; Páez 2009) even during the 2008 recession (e.g., Cho et al. 2011). These household preferences are unlikely to change appreciably even with the gradually diminishing preferences for bigger houses and larger lots among the aforementioned demographic groups. Thus, the recent decrease in sprawl may not have come from changes in household preferences but rather from external factors such as the recession and collapse in the real estate market.

As the U.S. economy has in the last four years experienced both the largest real estate boom and most severe housing slump in five decades, the present (2011) is a good time to evaluate potential policy tools that aim to contain sprawl. Accordingly, the objective of this research is to evaluate the effectiveness of alternative land-use policy tools for controlling development in a sprawling metropolitan area during two extreme market conditions (i.e., the 2004 –2006 and 2008–2009 time periods that are referred to as “boom” and “recession” periods, respectively). Specifically, two hypotheses are tested: (1) the alternative sprawl-management policies promote more compact and less leapfrogging development and (2) the effectiveness of the policies in controlling sprawl varies between the boom and recession periods. The likelihoods of a given parcel being developed during the boom and recession periods were estimated using separate discrete-choice models. The difference in the effectiveness of land-use policies during the boom and recession is tested by comparing the significance and signs of the land-use policy variables in the spatial probit models for the two extreme market conditions.

The key contribution of this research is to provide the first empirical evaluation of land-use policies for containing urban sprawl under different market conditions. An implicit assumption typically made in previous literature is that the effectiveness of policy tools is not evaluated under a recession or a boom (e.g., Brueckner and Kim 2003). Our research tests three types of land use policies to promote compact development and discourage leapfrogging development while acknowledging two extreme market periods. Two models, one for a boom (hereafter referred to as "the boom model") and another for a recession (hereafter referred to as "the recession model"), and their simulation results will reveal different effects of three land-use policies (i.e., urban growth boundary (UGB), agricultural zone, and property tax on land value, discussed below in the "*Spatial landscape pattern metrics with and without the policy variables*" section) on individual development decisions for the two extreme market conditions. These results will provide researchers, policy makers, and those who advise them a way to inform public policymaking in an important, useful, and easily understandable way.

Empirical Model

Extending Carrión-and Irwin (2004), a two-step approach is used that combines step (1) a parcel-level, spatial discrete-choice model (Klier and McMillen 2008) to explain individual land conversion decisions, and step (2) *ex ante* simulations of the spatial discrete-choice model with and without three specific land-use policies, assuming either a boom or a recession, to estimate the policy impacts on sprawl using spatial landscape pattern metrics.

Step (1): Spatial lag probit model for parcel-level land conversion decisions

Land conversion decisions may be co-determined through neighborhood spillover effects because neighbors share common characteristics and hence their decisions exhibit high dependence among the error terms in a land conversion model (Irwin and Bockstael 2001; Carrión-Flores and Irwin 2004; Cho, Newman and Wear 2005; Irwin, Bell and Geoghegan 2006). Spatial dependence can occur due to spatially correlated land-use decisions or as a consequence of residual correlation caused by unobserved factors that are spatially dependent.

The simple characterization of the development decision for a parcel of land depends on differences between the rent *R* from development *d* and no development *u* at parcel location *i*. A parcel of land is developed if:

(1) $$R_{id} > R_{iu}.$$

The probability that land parcel *i* is developed is a function of observable variables *X* and a random error ε:

(2) $$\Pr\left(\alpha_{id} X_{id} + \varepsilon_{id} > \alpha_{iu} X_{iu} + \varepsilon_{iu}\right).$$

The observed variables are location and neighborhood-specific factors determining rent, and the ε's are random disturbances reflecting an imperfect relationship between the local attributes and rents. It is likely that the rents from development and no development are codetermined as functions of rents occurring at other locations. Thus, the probability function (2) can be revised as follows:

(3) $$\Pr\left(\rho^{d} R_{-id} + \alpha_{id} X_{id} + \varepsilon_{id} > \rho^{u} R_{-iu} + \alpha_{iu} X_{iu} + \varepsilon_{iu}\right),$$

with ρ^{d} and ρ^{u} determining the degree of correlation between rents from development and no development at other locations *-i* (i.e., locations other than *i*), respectively. Thus, the probability that parcel *i* is developed is given by:

(4) $$\Pr(develop) = \Pr\left[(\rho^{d} R_{-id} - \rho^{u} R_{-iu}) + (\alpha_{id} X_{id} - \alpha_{iu} X_{iu}) > (\varepsilon_{id} - \varepsilon_{iu})\right].$$

Klier and McMillen (2008) provide the details for the estimation of equation (4) based on a spatial lag probit model. Using Klier and McMillen's (2008) notation, the covariance of the spatial lag land-development model for limited dependent response variables:

(5) $$Y^* = \rho \mathbf{W} Y^* + X\beta + \varepsilon,$$

is $\sigma_{\varepsilon}^{2}[(I-\rho\mathbf{W})'(I-\rho\mathbf{W})]^{-1}$, where Y* denotes the developed state (Y* = 1 if parcel is developed, 0 otherwise), **W** is a matrix representing the neighborhood structure (see detailed description in the *Specification of neighborhood structure* section below), and ρ is the coefficient of spatial lag to be estimated. Because the scale of Y cannot be identified in discrete choice models, σ_{ε}^{2} is restricted to be constant. For simplicity, notation for the two time periods is suppressed as the same model is applied to each time period (recession and boom periods). In the case of probit specification, $\sigma_{\varepsilon}^{2} = 1$, with the variance ($\sigma^2$) specified as the diagonal elements of the term.

Defining S to be an n by n matrix with σ_i^{-2} on the diagonals and letting ω_{ij} be an element in the n by n matrix $S(\mathrm{I} - \rho\mathbf{W})^{-1}$, the error terms for the latent variable model are:

(6) $$\varepsilon_i^* = \sum_{j=1}^{n} \omega_{ij}\varepsilon_{ij} .$$

The marginal probabilities of the spatial-probit model are calculated as:

(7) $$\partial E(\mathrm{Y} \mid \mathrm{X}) / \partial \mathrm{X} = \phi[(\mathrm{I} - \rho\mathbf{W})^{-1}\mathrm{I}\bar{\mathrm{X}}\beta] \odot (\mathrm{I} - \rho\mathbf{W})^{-1}\mathrm{I}\beta ,$$

where $\mathrm{X}, \bar{\mathrm{X}}, \phi(\cdot), \text{and} \odot$ denote the explanatory variable, the mean value of X, the standard normal density, and Hadamard or element-by-element multiplication, respectively. The diagonal elements are the direct effects, the average of the row sums are the total effects, and the differences between these two measures are the indirect effects (LeSage and Pace 2009, pp 293-297). The direct effect, which is equivalent to the marginal effect of traditional aspatial regression models, captures the marginal effect of an explanatory variable for observation *i* on the probability of observation *i* being developed. The indirect effect, which can be estimated only by the spatial model, captures the marginal effect of an explanatory variable for all neighboring observations (-*i*) on the probability of observation *i* being developed. The total effect, which is the sum of the direct and indirect effects, captures the overall effect for an explanatory variable of all observations in the neighborhood, including observation *i*, on the probability of observation *i* being developed. Thus, if ρ is statistically insignificant, the total effect has the same magnitude as the direct effect since the indirect effect can be regarded as zero.

Since unstable estimates and high standard errors are expected in regression results when multicollinearity exists in the model, variance inflation factors (VIFs) are used to detect potential collinear variables (Maddala 1992). VIFs are a scaled version of the multiple correlation coefficients between a single variable and the rest of the independent variables. A general rule of thumb is that multicollinearity may be a problem if the VIF is greater than 10 (Gujarati and Beck 1995).

Specification of the neighborhood structure

In general, there is no consensus as to which spatial weight matrix is most appropriate for any econometric study, and the selection of an appropriate spatial weight matrix **W** in equation (5) remains a challenge. Florax and Rey (1995) discuss problems that may arise if spatial weight matrices are poorly selected. In some empirical applications and in certain experimental settings (Florax and Nijkamp 2003), the choice of spatial weight matrix may lead to identification problems (Anselin 1988). Therefore, we test several types of spatial weight matrices, show how they influence model estimates, and select the spatial weight matrix with the best goodness of fit for both the recession and boom models.

In selecting a spatial weight matrix, we consider a variety of neighborhood specifications, including the Thiessen polygon ("queen" contiguity) and K-nearest neighbor (KNN) arrangements, and inverse distance matrices with the distance cut-off specified by the Thiessen polygon neighborhoods or KNN.[10] The Thiessen polygon spatial weight matrix, which effectively turns the spatial representation of a sample from points into areas, was constructed in two steps. In the first step, Thiessen polygons were

[10] A polygon is a plane figure that is bounded by a closed path. Thiessen polygons are polygons whose boundaries define the area that is closest to each point relative to all other points.

constructed so that the centroid of each parcel was assigned to an area whose boundaries are defined by the median distance between the centroid of a parcel and its nearest centroids of parcels. In the second step, the first-order contiguous Thiessen polygons were identified as observations that share a common border or vertex. **W** was structured so that, if parcels *i* and *j* were identified as neighbors, the off-diagonal elements of the spatial weight matrix $\mathbf{w}_{ij}$ took the value of 1, and 0 otherwise. The diagonal elements took the value of 0.

The KNN spatial weight matrix is based on the assumption that observations outside the KNN of any given observation have no influence on the given observation. It was constructed so that the number (*k*) of nearest neighbor parcels was identified based on the Euclidean distances between any two possible centroids of parcels. Given the identified KNN, **W** was structured the same way as the Thiessen polygon spatial weight matrix. Several numbers of neighbors (i.e., 1, 2, 3, 4, 5, 7, 11, 26, and 131 nearest neighbors) were used to construct the KNN spatial weights for use in estimation.

Each Thiessen polygon neighborhood or KNN was interacted with an inverse distance matrix to include decay effects between neighbors. The inverse distance spatial weight matrix was constructed so that Euclidean distances between any two possible centroids of parcels were measured and their inversed values within the distance cut-off specified by the Thiessen polygon neighborhoods or KNN were taken as the off-diagonal elements of the spatial weight matrix $\mathbf{w}_{ij}$. Again, the diagonal elements took the value of

0. All matrices were row standardized such that the column sum of each row was one. [11] The null hypothesis of a spatial lag autoregressive parameter equal zero was tested for the boom and recession models with all spatial weight matrices. The selection of spatial weight matrices was based on overall model fit including the log likelihood and McFadden R^2.

Specification of the parcel-level development model

One way to define residential development of land parcel *i* is to identify whether or not a structure for residential purposes has been built during a given period of time (e.g., Cho et al. 2010; Cho and Newman 2005; Cunningham 2006). Identifying the development status of a parcel based only on the placement of a structure on the parcel, regardless of the parcel's fragmentation status, presents problems in using the land conversion model to identify spatial patterns of land-use changes. Specifically, building a structure on a parcel within a developed subdivision does not represent new development and is not associated with the spatial pattern of land-use changes. Thus, for our purposes, a parcel with such construction should not be counted as a "developed" parcel in the land conversion model in equation (5). Another problem with the land conversion modeling approach based on the placement of a structure is that structures built on parcels within a

[11] By row-standardizing spatial weight matrix, we create proportional weights in cases where features have an unequal number of neighbors. While the number of neighbors is equal to *k* and the number of non-zero links in KNN weight, those numbers vary in the Thiessen polygon and hybrid weight matrices. Eigenvector offers an overview of spatial structure since these eigenvalues furnish distinct map pattern descriptions of latent spatial autocorrelation in georeferenced variables (Griffith 2000).

subdivision are counted as individual land-development decisions, when in fact development of a subdivision represents only one land-development decision by a landowner or a group of landowners.

The aforementioned issues can be mitigated by treating large parcels as development units that are in either a developed or an undeveloped state prior to subdivision fragmentation. Using this notion and following Irwin and Bockstael (2001) , we define Y in equation (5) as undeveloped parcels at the beginning of the study period that could have been developed for residential uses. At the beginning of the boom period and the recession period, the total numbers of parcels in Knox County were 155,614 and 185,641, respectively. Among these totals, parcels that had already been fragmented for subdivision development (51,956 and 54,017 parcels, respectively) were excluded from the data. In addition, parcels that were too small to affect spatial patterns of land-use changes (i.e., smaller than minimum size of subdivision development in 2004–2009, i.e. 0.5 acres—52,247 and 56,745 parcels, respectively) and parcels under zoning that neither allowed residential development nor rezoning for residential development (34,123 and 57,762 parcels, respectively) were also excluded from the data.[12] After excluding the aforementioned parcels, 17,288 and 17,117 parcels remained for use as developable

[12] In Knox County, the zones that allow residential development or rezoning for residential development by zoning ordinance include RAE (exclusive residential), RA (low density residential), RB (general residential), PR (planned residential), E (estate), and (A) agricultural zonings. The zones that allow neither residential development nor rezoning for residential development include OS (open space), CA (general business), CB (business and manufacturing), PC (planned commercial), SC (shopping center), CH (highway commercial), T (transition), CR (rural commercial), CN (neighborhood commercial), OA (office park), OB (office, medical, and related services), OC (civic and institutional), BP (business and technology park), EC (employment center), LI (light industrial), I (industrial), F (floodway), HZ (historical overlay), TO (technology overlay), and TC (town center) zones.

parcels at the beginning of the boom and recession periods, respectively. Some parcels in the data were entirely vacant while others had at least one structure.

Upon identifying the parcels with the potential to be developed for residential uses and possibly affecting the spatial pattern of land-use changes, the question remaining is how to define the developed ($Y = 1$) and undeveloped ($Y = 0$) states. A parcel that was fragmented for subdivision development during the periods, regardless of the existence of a structure on the parcel at the beginning of the periods, was defined as a developed parcel (hereafter referred to as "subdivision development"). A parcel that was not fragmented during the periods was defined as an undeveloped parcel. The un-fragmented parcels defined as undeveloped parcels can be grouped into four types: (1) parcels where at least one structure existed at the beginning of the periods that had structures built during the periods, (2) parcels where at least one structure existed at the beginning of the periods that had no structure built during the periods, (3) vacant parcels at the beginning of the periods that had structures built during the periods, and (4) vacant parcels at the beginning of the periods that had no structures built during the periods.

Defining parcel types (2) and (4) as undeveloped parcels is not complicated since no structures were built on the parcels during the periods. In contrast, defining parcel types (1) and (3) as undeveloped parcels is more complicated. There is, unfortunately, no clear-cut answer to defining parcel types (1) and (3) as either developed or undeveloped parcels; our rationale for defining them as undeveloped parcels was determined by the likelihood that newly built structures during the periods could potentially affect the spatial pattern of land-use changes. Specifically, parcels of type (1) are typically associated with adding structures or rebuilding, and neither of these activities affects spatial patterns of land-use changes as long as they do not contribute to fragmentation of the parcels. Parcels of type (3) are typically large. These parcels were considered undeveloped because they could be fragmented into subdivisions even though a structure (e.g., large-lot, single-family housing unit) existed on the parcels at the beginning of the periods. Thus, considering these as developed parcels may bias the spatial pattern of land-use changes, because such parcels would likely contain significant amounts of open space that could be fragmented into subdivisions.

Step (2): Spatial landscape pattern metrics with and without the policy variables

To measure how the policy variables affect land use patterns during the economic boom and recession, subdivision development is predicted with and without the policy variables using the parameter estimates from the boom and recession models. This forecast facilitates *ex ante* comparisons between the predicted development pattern with *status quo* polocy variables (hereafter referred to as "baseline prediction") and the predicted development pattern without them.

The hypotheses that the three policy tools decrease fragmented development at the county level are tested by comparing three landscape pattern metrics: the number of patches (i.e., the total number of contiguous residential developments), the mean patch size (i.e., average size of contiguously developed residential patches), and the total edge length (i.e., the total perimeter of contiguously developed residential patches) with and without the three land use policy variables.[13] The hypotheses that the three policy tools reduce the leapfrogging pattern of development and increase the compact pattern of development at the county level are tested by comparing two landscape pattern metrics: mean nearest neighbor (i.e., average of distances of residential patches to their nearest neighbor) and mean perimeter-area ratio (i.e., sum of the perimeters of residential patches divided by the number of residential patches) with and without the three land use policies, providing an indication of the dispersion of developed patches. In sum, the effectiveness of the policy variables between the two periods was tested by comparing the five landscape pattern metrics with and without the three land use policies for the boom and recession models.

Study Area and Data

The study area is Knox County, Tennessee, which covers 526 square miles in East Tennessee and had a population of approximately 436,000 in 2009 (U.S. Census Bureau 2010). Three major GIS data sets were used: individual parcel data, census-block group data, and environmental feature data. Detailed descriptions and statistics of the individual variables used in the regressions are reported in Table 5. Individual parcel data as polygon shape files were obtained from the KGIS (Knoxville Knox County, Knoxville

[13] Areas fragmented by local roads of width smaller than 20 feet were considered continuous residential patches. The landscape pattern metrics were created using the GIS shape files of individual parcel data and the Patch Analyst tool in ArcGIS 9.3 (Rempel 2011).

Utilities Board Geographic Information System) and the Knox County Tax Assessor's Office. Individual parcel data include attribute tables showing information about development status, location information of parcels (i.e., UGB, agricultural zone, City of Knoxville, Town of Farragut, and high school district), assessed land value, and parcel size. Since no parcel was developed inside the City of Knoxville during the recession period, the dummy variable for the City of Knoxville was excluded from the recession model to obviate complete separation, which would have caused a serious problem in model validity.

Environmental feature data (i.e., park, golf course, greenway, railroad, highway, water body, and sidewalk) and location of the central business district (CBD) were obtained from KGIS (2006) and Environmental Systems Research Institute Data and Maps 2008 (Environmental Systems Research Institute 2008) to create distance variables. The elevation data were obtained from the US Geological Survey (U.S. Geological Survey 2009) and were calculated at a resolution of 1/3 arc-second (approximately 100 square meters), a scale sufficiently small to account for the smallest parcels (about 2,000 square meters). The slope was derived from a digital elevation model using the elevation data (U.S. Geological Survey 2001). American College Testing (ACT) scores for the 12 high school districts were obtained from the Tennessee Department of Education (TDE 2009) and used as proxies for school quality. The ACT scores at the beginning of each study period were assigned to parcels in each high school district. The census-block group data from the 2000 Census, including median household income, housing density, travel time to work, unemployment rate and vacancy rate, were assigned to parcels within their census-block groups. The periodic nature of census taking means that the census and parcel records are not perfect matches; consequently, the census data were treated as time-lagged variables.

Sprawl-management policies that could be used in the area include urban growth boundary (UGB) representing development guidelines, agricultural zone representing zoning ordinances, and property tax on land value representing incentive-based policies. Knox County, Tennessee adopted an UGB in 2001. The UGB covers about 42 square miles located mostly around the outside boundary of the City of Knoxville. The land within the UGB is reasonably compact but adequate to accommodate the city's expected growth over the next 20 years (Knoxville/Knox County Metropolitan Planning Commission 2006). The agricultural zone covers about 300 square miles, mostly outside the City of Knoxville. It separates farming activities from conflicting non-farm land uses to protect a critical mass of farms and farmland (Cordes 2001). Knox County uses the same property tax rate (i.e., 2.96% for the 2004–2006 period and 2.69% for the 2008–2009 period) on the values of land and structure when levying property taxes on residential property. A change in the burden of property taxation on land value is tested as a sprawl policy to promote greater economic incentive to develop land around existing infrastructure and related amenities where land values are higher, and simultaneously to discourage development in areas distant from infrastructure (Brueckner and Kim 2003).

Thus, UGB and agricultural zoning dummy variables and a property tax on land value represent the three policy tools.[14]

Empirical Results

Step (1): Spatial lag probit model for parcel-level land conversion decisions

The ranges of VIfs were, respectively, 1.23 to 2.96 and 1.11 to 3.62 for the boom and recession models, which suggest no serious collinearity among explanatory variables since it does not significantly increase the variance of an estimated regression coefficient.

The choice of spatial weight matrix has little effect on the overall measures of goodness of fit (i.e., log likelihood and McFadden R^2) for the spatial lag probit models (Table 6). These results are encouraging, suggesting that the specification of neighborhood structure does not appear to be a critical factor in model identification. The ranges of log likelihoods were -451 to -381 and -225 to -189 for the boom and recession models, respectively, and the McFadden R^2 measures were 0.30 to 041 and 0.19 to 0.32 for the boom and recession models, respectively. Given these results, the spatial lag autoregressive (AR) probit was estimated using the row standardized, KNN (2) specification.

For all spatial weight matrices, the null hypothesis that the spatial lag autoregressive parameter is zero was rejected at the 5% level for the boom model

[14] A property tax on structure value was not considered because most undeveloped parcels in this study were large vacant parcels without structures as the boom and recession periods began.

whereas it was not rejected for the recession model, suggesting that the positive spatial clustering occurring during the boom dissipated during the recession. This result suggests less spatial dependence in subdivision development during the recession compared to the boom. The finding implies that decision process was interacted with their neighbors during the real estate boom while it was not during the recession since relatively loose banking policies and easy lending during a boom than a recession encouraged landlord to be easily inspired by development decision of their neighbor during the boom.

Table 7 presents the parameter estimates of the spatial lag probit models for parcel-level land conversion decisions. The variables that were statistically significant at the 5% level are denoted with asterisks in the table and are referred to as “significant” in the discussion below. Parcels in census blocks with lower unemployment rate and lower vacancy rate were more likely to be developed for subdivisions during the recession, but the effects of these variables were not significant in the boom model. The difference in the significance of these variables between the two periods suggests that subdivision development decisions were more sensitive to socioeconomic signals in some areas than in other areas during the recession than the boom.

The parameters for the distance to golf course and the distance to greenway were negative and significant for both periods. Negative signs for these variables indicate that subdivision developments occurred more frequently in areas closer to golf courses and greenways regardless of economic condition. Thus, green open space and recreation accessibility provided by golf courses and greenways were recognized as attractive factors for new subdivision development in both periods. During the economic recession, greater distance to water bodies was associated with higher probability of subdivision development. Because a water body typically provides a positive amenity, less subdivision development of parcels closer to water bodies is unexpected. The unexpected relationship may be associated with the demand for subdivision development of parcels with a water-view amenity being lower during the recession relative to parcels without a premium view amenity (Cho, Kim and Roberts 2011). The lower demand for the development of parcels with a water-view amenity during the recession may be explained by the diminished affordability of these parcels due to significantly diminished disposable income during the recession. The negative effects of proximity to water bodies may be explained by the fact that undeveloped land closer to water bodies was already developed prior to the boom.

All other significant coefficients have their expected signs. During the economic boom, a decrease in slope, an increase in lot size, and parcels outside of the Town of Farragut, with less urban and more rural characteristics, increased the probability of development. These results may be caused by residents' and developers' preferences for bigger houses, larger lots, and lower land prices that drive urban sprawl during an economic boom. Subdivision development was more likely to have occurred in parcels in high school districts with higher ACT scores (possibly reflecting higher quality schools) during both periods. The consistently positive effect of ACT scores implies the importance of school quality in subdivision development regardless of economic conditions.

Effects of policy variables on subdivision development

Agricultural zoning and the property tax on land value significantly affected subdivision development during the economic boom whereas agricultural zoning was the only significant policy variable during the economic recession. The consistently negative effects of agricultural zoning during both periods suggest that parcels in agricultural zones were less likely to be developed than other parcels regardless of market status. This finding implies that agricultural zoning is an effective tool for mitigating development, irrespective of economic conditions. Agricultural zoning is a barrier to residential subdivision development because parcels in an agricultural zone require the approval of rezoning petitions, demanding a great deal of time and effort (Cho et al. 2010).

The insignificant effects of UGB on subdivision development in both models correspond with previous findings that UGBs have no impact on land development in Knoxville (e.g., Cho et al. 2007; Jun 2004), whereas they are contrary to the results of other studies suggesting that UGBs effectively inhibit sprawl (e.g., Kline 2005; Kline and Alig 1999; Nelson and Hellerstein 1997; Patterson 1999). An UGB is a regional boundary, set in an attempt to control urban sprawl by mandating that the area inside the boundary be used for higher density urban development and the area outside be used for lower density development; however, the UGB in Knoxville does not effectively differentiate between development requirements inside and outside the boundary. Based on interviews with planners and researchers engaged in the Knoxville UGB planning process, enforcement of different development requirements does not exist between areas within or without the boundary, leading to the UGB having little impact on subdivision development.

The significantly positive effect of the property tax on land value on the decision to develop subdivisions during the economic boom suggests that an increase in the tax on land value of undeveloped parcels increases the probability of residential development. This finding is consistent with the finding that higher taxes on land value promote greater economic incentive to develop land where land values are higher while higher taxes discourage development of land where land values and their corresponding taxes are low (e.g., Brueckner 1986; Brueckner and Kim 2003; Case and Grant 1991; Mills 1998; Nechyba 1998; Oates and Schwab 1997; Skaburskis 1995; Cho et al. 2010). However, the property tax on land value did not have the same effect on decisions to develop subdivisions during the economic recession. This contrasting result is interesting in the sense that the insignificance of the tax on land value as a potential policy tool to promote compact development during the economic recession emanates from the burden of the recession, which shrinks housing demand, overshadowing the burden of higher taxes on land values, which results in ineffective pressure on development.

The direct, indirect, and total effects of significant policy variables on subdivision development described in equation (7) are presented in the Table 8. The agricultural zone had direct and indirect effects in the boom model of -0.210 and -0.153, respectively. The sum of these effects (total effect) suggests that a parcel within an agricultural zone had a 36.3 percent lower probability of subdivision development than a parcel not zoned agricultural. The property tax on land value had direct and indirect effects in the boom model of 0.00506 and 0.00240, respectively. The total effect suggests that a $100 increase in the tax on land value would increase the overall probability of subdivision development by 0.746 percent. Since the spatial lag autoregressive coefficient was not significant in the recession model, the total effect of the agricultural zone (-0.227) is the same as the direct effect which estimated in aspatial probit, which is similar to the direct effect of the agricultural zone during the boom period (-0.210). The total effect of the agricultural zone suggests that an agriculturally zoned parcel has a 22.7 percent lower probability of subdivision development during the recession compared with a non-agriculturally zoned parcel. The insignificant indirect effect suggests that the clear pattern of spatial spillover among agricultural zones during the boom dissipated during the recession. The dispersed spatial-spillover effects among agricultural zones during the recession contrasts with a less concentrated pattern of spatial dependence in subdivision development during the recession.

Spatial landscape pattern metrics with and without the policy variables

The spatial configurations of residential lands with and without *status quo* zoning and tax are presented in Table 9. Henceforth, the comparison of spatial configurations is highlighted in the discussion below when the difference between the two is greater than 1%. The boom and recession models predicted (1) increases in the number of patches of residential parcels due to agricultural zoning of roughly 7% and 1%, respectively, and (2) decreases in the mean patch size of residential parcels due to agricultural zoning by roughly 13% and 1%, respectively. The boom model predicted (1) decreases in the total edge length of residential parcels due to agricultural zoning by roughly 2% and (2) increases in the mean nearest neighbor of residential parcels due to agricultural zoning by roughly 2%. Thus, the predicted landscape pattern matrices during the boom showed that the pattern of subdivision development was inconclusive in terms of fragmented development due to agricultural zoning, but more dispersed. The predicted landscape pattern metrics during the recession showed that the pattern of subdivision of development was more fragmented with smaller sized parcels. These outcomes imply a rejection of the hypothesis that agricultural zoning promotes less fragmented, more compact, and less leapfrogging development during both the boom and recession periods. These effects vary depending on market conditions.

The boom model predicted (1) a 1% decrease in the number of patches of residential parcels, (2) a 1% increase in the mean patch size of residential parcels, and (3) a 1% decrease in the mean perimeter-area ratio of residential parcels due to the property tax on land value. These results suggest that the predicted pattern with the property tax on land value was less fragmented, with larger sized subdivisions, and more compact due to the property tax on land value during the boom period. These outcomes indicate that the following hypotheses should not be rejected: (1) the property tax on land value promotes less fragmented, more compact, and less leapfrogging development and (2) the effectiveness of the property tax on land value in promoting more compact and less leapfrogging development varies between boom and recession periods.

Conclusion

As a case study, the following hypotheses were tested: (1) UGB, agricultural zone, and property tax on land value (the three land-use policy variables) promote more compact and less leapfrogging development and (2) the effectiveness of the three land-use policy variables in controlling sprawl varies between real estate boom and recession periods. These hypotheses were tested by comparing landscape pattern metrics with and without the three land-use policy variables for boom and recession periods. The comparisons were based on spatial lag probit models for parcel-level land conversion decisions.

In summary, (1) a property tax on land value promotes more compact and less leapfrogging development during the boom, (2) zoning of land for agricultural use is an effective tool for mitigating residential development in general during the boom and recession, but does not encourage more compact and less leapfrogging development during either period, and (3) the UGB does not affect development nor the spatial pattern of development during the boom or the recession. These findings are interesting in the sense that the influence of the land use policy variables depends not only on the kind of land-use policy but also the economic context under which the policies are implemented.

The effectiveness of the property tax on land value found in this research confirms the results of previous literature that incentive-based policies, such as changes in the tax on land value, can be effective land-use policy tools (e.g. Bengston et al. 2004; Cho et al. 2003; Mayer and Somerville 2000; Wu and Cho 2007). The effectiveness of the property tax on land value during the boom and not the recession can be explained as follows. When the property tax on land value of vacant parcels is increased, the higher land tax motivates landowners to generate income to pay the tax (Cho, Kim and Roberts 2011) such as the land owner can reduce the tax burden by developing the vacant parcels to earn income. The greatest economic incentive to develop land typically exists adjacent to preexisting development where land values are highest, while areas far from preexisting development have less economic incentive for development (Rybeck 2004). Consequently, the higher land tax encourages more compact and less leapfrogging development during a boom. In contrast, no such effect was found during a recession when the income potential of development is lower and more risky.

Ancillary findings included the difference in the spatial spillover effect of development identified by the spatial lag autoregressive coefficient in the spatial lag land-development models and the difference in the significance of socioeconomic variables between the two periods. We found that the spatial spillover effect was significant during the boom but dissipated during the recession. In addition, subdivision-development decisions were more sensitive to socioeconomic market signals (i.e., unemployment rate and vacancy rate) during the recession than during the boom. These findings may be explained by development decisions being less sensitive to socioeconomic market signals during a boom because of looser banking policies and easier lending during a boom than a recession.

Table 5. Variables and Definition

Variables (Unit)	Definition	Boom	Recession
Dependent variable			
Development	Dummy variable indicating development status of parcel (1 if a parcel was fragmented for subdivision development in 2004-2006 for the boom or in 2008-2009 for the recession, 0 otherwise)	0.006 (0.078)	0.002 (0.048)
Policy variables			
Urban growth boundary (UGB)	Dummy variable for UGB (1 if a parcel was within UGB, 0 otherwise)	0.097 (0.296)	0.096 (0.295)
Agricultural zone	Dummy variable for agricultural zone (1 if a parcel was within an agricultural zone, 0 otherwise)	0.988 (0.108)	0.992 (0.087)
Property tax on land value ($)	Property tax on land value	750.735 (760.709)	682.496 (695.038)
Socioeconomic variables			
Median household income ($)	Median household income for census-block group in 2000	20,566.552 (7,198.918)	20,521.296 (7,176.327)
Housing density (houses/acre)	Housing density for census-block group in 2000	0.308 (0.330)	0.304 (0.321)
Travel time to work (Minutes)	Average travel time to work for census-block group in 2000	25.980 (3.965)	26.003 (3.962)
Unemployment rate	Unemployment rate for census-block group in 2000 (ratio of unemployed to the labor force, age 16 or older)	0.037 (0.021)	0.037 (0.021)
Vacancy rate	Vacancy rate for census-block group in 2000 (ratio of vacant housing units to total housing units of any type)	0.067 (0.021)	0.067 (0.021)
Distance and physical variables			
Distance to park (feet)	Euclidean distance from the centroid of a parcel to the centroid of the nearest park	29,468.632 (14,164.907)	29,587.551 (14,149.714)

Table 5 Continued

Variables (Unit)	Definition	Boom	Recession
Distance to golf course (feet)	Euclidean distance from the centroid of a parcel to the nearest golf course	17,874.082 (8,120.861)	17,929.983 8,128.046)
Distance to greenway (feet)	Euclidean distance from the centroid of a parcel to the nearest greenway	18,559.659 (9,555.118)	18,648.959 (9,538.317)
Distance to railroad (feet)	Euclidean distance from the centroid of a parcel to the nearest railroad	12,635.939 (8,791.858)	12,683.234 (8,798.126)
Distance to highway (feet)	Euclidean distance from the centroid of a parcel to the nearest interstate highway	20,052.652 (12,980.273)	20,127.714 (12,995.385)
Distance to water body (feet)	Euclidean distance from the centroid of a parcel to the nearest water body	11,361.189 (8,208.319)	11,378.740 (8,222.779)
Distance to sidewalk (feet)	Euclidean distance from the centroid of a parcel to the nearest sidewalk	12,167.181 (9,618.737)	12,237.390 (9,623.790)
Distance to CBD	Euclidean distance from the centroid of a parcel to the centroid of the central business district (CBD)	53,534.129 (16,969.032)	53,534.978 (16,941.097)
Elevation	Average elevation of a parcel	3,400.825 (386.741)	3,400.960 (387.529)
Slope (°)	Degree of slope at the parcel location	7.741 (4.434)	7.759 (4.442)
Lot Size (Acre)	Size of residential parcel	5.434 (13.044)	5.239 (12.401)
Spatial fixed effect Variables			
ACT score	Average composite score of American College Test (ACT) by high school district in 2004 for the boom and in 2008 for the recession	20.542 (0.717)	21.160 (1.015)
Knoxville	Dummy variable for City of Knoxville (1 if a parcel was within City of Knoxville, 0 otherwise)	0.026 (0.160)	
Farragut	Dummy variable for Town of Farragut (1 if a parcel was within Town of Farragut, 0 otherwise)	0.004 (0.059)	0.003 (0.051)

Table 6. Model Selection Criteria

Spatial weight matrix	Boom		Recession	
	Log likelihood	McFadden R^2	Log likelihood	McFadden R^2
Queen Contiguity	-384.239	0.400	-189.349	0.315
K nearest neighbors of order q [KNN(q)]	-380.595	0.410	-188.957	0.316
KNN(1)	-391.940	0.388	-190.568	0.310
KNN(2)	-380.595	0.410	-188.957	0.316
KNN(3)	-383.965	0.401	-201.318	0.271
KNN(4)	-404.166	0.369	-225.055	0.185
KNN(5)	-399.370	0.377	-195.878	0.291
KNN(7)	-387.362	0.395	-192.261	0.304
KNN(11)	-383.102	0.402	-190.802	0.309
KNN(26)	-383.788	0.401	-190.647	0.310
KNN(131)	-383.788	0.401	-190.647	0.310
Hybrid with inverse distance (ID)				
KNN(1) × ID	-391.940	0.388	-190.568	0.310
KNN(2) × ID	-396.106	0.382	-199.495	0.278
KNN(3) × ID	-391.315	0.389	-204.019	0.261
KNN(4) × ID	-397.006	0.380	-209.562	0.241
KNN(5) × ID	-399.370	0.377	-206.112	0.254
KNN(7) × ID	-423.095	0.340	-209.291	0.242
KNN(11) × ID	-451.135	0.296	-195.839	0.291
KNN(26) × ID	-415.882	0.351	-190.313	0.311
KNN(131) × ID	-383.921	0.401	-189.743	0.313
Queen Contiguity × ID	-384.239	0.400	-189.349	0.315

Note: Aspatial probit log likelihood = -640.580 (boom) and -276.242 (recession).

Table 7. Parameter Estimates for the Spatial Lag Probit Models

Variables (Unit)	Boom		Recession	
	Coefficient	Std. Error	Coefficient	Std. Error
Constant	-1.791	8.165	-0.108	8.423
Policy variables				
Urban growth boundary	0.316	0.182	0.318	0.244
Agricultural zone	-1.403*	0.152	-1.482*	0.280
ln(Property tax on land value)	0.173*	0.059	0.120	0.099
Socioeconomic variables				
ln(Median household income)	-0.488	0.270	0.163	0.340
Housing density	0.049	0.109	0.087	0.198
Travel time to work	0.049	0.026	0.039	0.026
Unemployment rate	-4.473	3.828	-11.802*	5.355
Vacancy rate	-1.772	1.919	-7.355*	3.601
Distance and physical variables				
ln(Distance to park)	-0.001	0.159	-0.126	0.180
ln(Distance to golf course)	-0.314*	0.124	-0.291*	0.127
ln(Distance to greenway)	-0.340*	0.077	-0.308*	0.093
ln(Distance to railroad)	-0.030	0.057	0.024	0.087
ln(Distance to highway)	0.183	0.105	0.189	0.098
ln(Distance to water body)	0.004	0.112	0.191	0.104
ln(Distance to sidewalk)	0.039	0.095	0.190	0.123
ln(Distance to CBD)	0.121	0.219	-0.588	0.359
ln(Elevation)	-0.070	0.811	-0.722	0.953
ln(Slope)	-0.140*	0.031	-0.064	0.081
ln(lot size)	0.602*	0.093	0.497*	0.083
Spatial fixed effect Variables				
ACT score	0.327*	0.127	0.421*	0.119
Knoxville	0.299	0.263		
Farragut	-1.131*	0.458	-0.308	0.470
Spatial lag				
ρ	0.229*	0.097		

* Significant at the 5% level (p<0.05).

Table 8. Marginal Effects of Policy Variables Based on the Estimates of the Spatial Lag Probit Models

Variables	Marginal effect	Boom	Recession
Urban growth boundary	Direct effects	0	0
	Indirect effects	0	0
	Total effects	0	0
Agricultural zone	Direct effects	-0.210	-0.227
	Indirect effects	-0.153	0
	Total effects	-0.363	-0.227
Property tax on land value	Direct effects	0.506	0
($\times 10^{-2}$)	Indirect effects	0.240	0
	Total effects	0.746	0

Table 9. ***Ex Ante*** **Comparisons between Predicted Development Patterns With and Without** ***Status Quo*** **Agricultural Zone And Propety Tax On Land Value**

Landscape Pattern Metrics		Boom	Recession
Number of patch [1]	*Status quo*	2,105	2,085
	Without agricultural zone	1,960	2,069
	Without property tax on land value	2,121	
Mean patch size [2] (acre)	*Status quo*	68.5	69.4
	Without agricultural zone	78.7	70.3
	Without property tax on land value	67.6	
Total edge length [3] (mile)	*Status quo*	3,190	3,184
	Without agricultural zone	3,262	3,187
	Without property tax on land value	3,198	
Mean Nearest Neighbor [4]	*Status quo*	2,194	2,195
(feet)	Without agricultural zone	2,147	2,197
	Without property tax on land value	2,192	
Mean Perimeter-Area Ratio [5]	*Status quo*	0.010933	0.010823
	Without agricultural zone	0.010919	0.010838
	Without property tax on land value	0.011026	

[1] Total number of contiguously developed residential patches.

[2] Average size of contiguously developed residential patches.

[3] Total perimeter of contiguously developed residential patches.

[4] Average of the distances from individual patches of residential land to their nearest neighbor (edge to edge).

[5] Sum of the perimeter/area ratios of residential patches divided by the number of patches.

CHAPTER III

EFFECTS OF SATISFACTION OF RECREATION INFORMATION AVAILABILITY ON CONSUMER WELFARE: A CASE STUDY OF THE ALLEGHENY NATIONAL FOREST

Abstract

This research estimates the change in consumer welfare due to higher satisfaction of recreation information availability using on-site sample data collected from the Allegheny National Forest. The marginal effect of satisfaction of recreation information availability on the number of visits to the site was positive and significant. *Ex ante* simulation showed that individual annual per capita consumer welfare was increased when perfectly satisfied recreation information availability was assumed hypothetically. Thus, under the assumption that providing quality information about recreational activities increases visitor satisfaction, quality recreational information promotes higher social welfare among visitors. The results can be useful for budget decisions with regard to the providing of quality recreation information.

Introduction

The United States is home to many excellent national parks and forests and state parks and forests. While it is clear that visitors to recreation sites benefit from the experience, it is not clear how much they benefit from the provision of those recreation sites. To examine the issue, this study uses the travel cost model, which measures the benefits provided by recreation sites based on the observed travel cost and was first described by Hotelling (1947). Economists have applied the travel cost model frequently to measure recreation demand (Trice and Woods 1958; Clawson 1959; Smith 1989). The travel cost model assumes that people travel to a recreation site if the marginal value of the site is at least as high as the marginal cost of traveling to the site. The demand curve for a given recreation site is determined based on the number of visits to the site from various distances with different travel costs. From the demand curve, "consumer welfare" reflects the difference between the value of the consumer's trip to the site and the cost required to take the trip (Gum and Martin 1977). Aggregating individual consumer welfares over the population in the relevant geographic area (area near the recreation site, e.g., metropolitan areas close to the site, counties surrounding the site, concentric circles around the site, and areas within a day's drive of the site) serves as a proxy for the site's market price (Champ, Boyle and Brown 2003; Heberling and Templeton 2009).

Information regarding site resources (e.g., proximity, access, conditions, facilities, and available special events) is one of the important factors that can shift a recreation site's demand curve and thus change consumer welfare (Reynolds and Braithwaite 2001). Increasing the flow of information relating to the use of recreation sites (e.g., available activities and facilities, overall usage, and current condition) can encourage people to use recreation sites more uniformly and efficiently, maximizing the use of the site by visitors (Lime and Stankey 1971). For example, results from a 2004 community survey showed that the satisfaction from visiting Lake Oroville in California depended not only on the physical condition of the lake but also the availability of information about recreation opportunities, facilities, and water level (Mayes, Vogel and Lienemann 2004). Results from a more recent survey identified the availability of recreation information as an important factor in promoting the demand for outdoor recreation in regional parks around the metropolitan area of Vancouver, Canada (LEES + Associates, Mustel Group and Urban Futures 2011).

Despite this documented influence of site information on recreation changes due to imperfect information about recreation sites, changes in consumer welfare due to imperfect information about recreation sites (which may be viewed as non-market goods) have not been explored in the travel cost model. On the contrary, the effects of imperfect information on consumer welfare have been closely examined in the related arena of market goods (Nelson 1970; Shapiro 1982; Kahn 1995). Hunter (2001) derived a simple model to measure the loss in consumer welfare that arises when consumers have imperfect information about price or quality of goods. Because of the cost of gathering information, consumers may face prices and quantities that deviate from equilibrium levels. For example, Mazzocchi et al. (2004) empirically showed that Italian consumers experienced welfare losses in the beef market due to a lack of information about a possible link between bovine spongiform encephalopathy (“mad-cow disease”) and Creutzfeldt-Jakob disease (sometimes called a human form of the disease). However, the welfare consequences of insufficient information about quality are ambiguous despite a widely held intuitive belief that imperfect information causes quality of goods to deteriorate (Shapiro 1982). Insufficient information about quality can increase or decrease demand when consumers overestimate or underestimate the quality of goods because they have imperfect information.

The objective of this research is to estimate the effect on consumer welfare from improved satisfaction of recreation information availability (hereafter referred to as “information satisfaction”) as a proxy measurement for the quality of recreation information availability. Specifically, the hypothesis that an improvement in the information satisfaction increases the number of visits and consumer welfare of recreation site visitors is tested. The hypothesis is based on the conceptual notion that higher information satisfaction is likely to stimulate greater willingness to visit the site, if travel costs are unchanged (Domestic Policy Council 1998). The results from this research can contribute to recreation management decisions. For example, having estimates of the impacts on consumer welfare of higher information satisfaction could be useful to recreation site managers trying to justify budget allocations for providing recreation information in increasingly tight times.

The remainder of the paper is organized as follows. First, the area under study, the Allegheny National Forest in northwestern Pennsylvania, and the data are described. The methodological challenges associated with the individual travel cost model are briefly discussed. Next, the individual travel cost model that addresses all the methodological challenges is described, followed by a presentation of the analytical results. The paper ends with a summary and concluding remarks.

Study Area and Data

In 1911, the United States Congress passed the Weeks Act, allowing the federal government to buy land in eastern states for the establishment of national forests (Whitney 1990). The Allegheny National Forest was established in 1923 and is located in northwestern Pennsylvania, covering 512,998 acres of land. Recreation in the Allegheny National Forest focused mostly on dispersed activities like hunting and fishing in the 1920s. Since then, improved facilities such as campgrounds with electricity, areas to watch wildlife, and trails for cross-country skiing and motorized recreation have been added to the area.

The National Visitor Use Monitoring (NVUM) survey has been conducted in a 4-year cycle by the U.S. Forest Service for 120 national forests (or combinations thereof) in the United States since 2000. The individual travel cost model was applied using data from NVUM (NVUM 2003). The NVUM project provided individual on-site survey sampling data for the Allegheny National Forest in 2001 and 2005.

The NVUM survey's purpose was to develop reliable estimates of recreation use of National Forest System lands through a nationally consistent, statistically valid sampling approach (White and Wilson 2008). Survey respondents were asked by the NVUM to report the number of visits they made to an area during the past 12 months for an individual or group. Since the current visit at the date of survey should be included as one visit, one is added to the number of visits indicated by respondents. To calculate round-trip travel cost to the Allegheny National Forest and other substitutable national, state, and local levels of parks and forests, round-trip travel distances (in miles) to both the Allegheny National Forest and other substitutable sites were measured using ArcMap 9.2 (Environmental Systems Research Institute 2009). Information about respondents' home locations was collected at the zip-code level in NVUM. The locations of the Allegheny National Forest and other substitutable national, state, local levels of parks and forest were determined by ESRI data and maps (Environmental Systems Research Institute 2004). The round-trip travel distances were multiplied by $0.14/mile, the reimbursement rate for charitable organizations specified by the Internal Revenue Service (IRS 2004), to generate round-trip travel cost.

The IRS has three different standard mileage rates separately for business, for medical or moving, and for charitable purposes. The standard mileage rates for charitable and for medical and moving purposes have traditionally been set lower than the rate for business purposes, reflecting only the "variable costs" of using an automobile, excluding the "fixed costs." Variable costs include gasoline, oil, maintenance, and tires and tire repairs; they also vary in proportion to miles driven, while fixed costs include the ownership expenses of depreciation, license and registration fees, and insurance. Since actual travel expenses were not available from the survey data, the smallest of the three rates (charitable contributions) was chosen as a proxy for travel cost to provide conservative estimates of the welfare impacts.

Four different site types exist in the Allegheny National Forest (i.e., day-use developed sites, overnight-use developed sites, wilderness sites, and general forest area sites).[15] The site types at their survey locations were assumed to be associated with their primary recreation uses. In addition, NVUM provided information about individuals' or groups' basic characteristics, such as the number of accompanying children under 16 years old and the total number of accompanying people. The dummy variable for the visitors' satisfaction of recreation information availability was created based on the information from NVUM (i.e., 1 if "satisfied" or "very satisfied," 0 otherwise). Visitors to the Allegheny National Forest were given surveys to complete each month from October 2000 through September 2001 and from October 2004 through September 2005, respectively. After incomplete survey responses were removed, 133 and 214 observations were available for analysis.

Methodological Challenges Associated with the Individual Travel Cost Model

There are well-known methodological challenges associated with the individual travel cost model using on-site sample data. The first methodological problem is how survey outliers

[15] Day-use developed sites (DUDS) include picnic sites, fish viewing sites, fishing sites, interpretive sites, observation sites, playground-park sport sites, ski areas, wildlife viewing sites, caves, visitor centers, museums, and swimming areas. Overnight-use developed sites (OUDS) include campgrounds, fire lookouts and cabins, hotels, lodges, and resorts, horse camps, organization sites, and any other overnight developed sites within Forest Service jurisdiction, whether managed by the agency or by a concessionaire. Wilderness (WILD) includes lands and waters that are part of the National Wilderness Preservation System. General forest area (GFA) includes all of the residual parts of a national forest not included in DUDS, OUDS, or WILD categories. Sample locations for general forest areas are at trailheads.

can be handled. In recreation-area use analysis, long-distance visits are likely to be multi-purpose while short-distance visits are likely to be single-purpose (Lue, Crompton and Fesenmaier 1993). However, because the individual travel cost model assumes that trips are taken only for the use of the recreation site and not for other purposes, the individual travel cost model with long-distance visits likely violates such assumptions and thus long-distance visits have to be treated as outliers (Smith and Kopp 1980). For example, Hellerstein (1991) suggested 1,000 miles as a reference threshold to judge outliers that are "too far" from the recreation site.

The second methodological problem was how other substitute recreation sites could be accommodated in the travel cost model. The demand for a recreation site is conceptually defined as a function of the site price, the site's characteristics, and the prices of all other substitute recreation sites in the individual travel cost model (Rosenthal 1987; McConnell, Bockstael and Strand 1991). Thus, a general method to allow substitutability is to include a vector of self-assessed prices of substitute recreation sites as explanatory variables (e.g., Keske and Loomis 2007; Starbuck et al. 2006). However, including self-assessed prices of substitute sites is often problematic because of the difficulty of obtaining such information from on-site surveys. Many times, a majority of survey respondents fail to answer the questions relating to self-assessed visit prices of substitute recreation sites (Willis and Garrod 1991). Previous studies found that a model that omitted substitute prices might bias the own price coefficient, which, in turn, may bias the welfare estimate of a price change (Gum and Martin 1975; Henderson 1991; Levine 1999; Brasington and Hite 2005).

The third methodological problem is an econometric issue associated with on-site sample data, i.e., over-sampling of frequent visitors and non-zero and non-negative integer values of the number of visits as a dependent variable. An individual travel cost model accommodating unique characteristics of on-site survey data has evolved as analyses using the individual travel cost model grow. The bias introduced by on-site sampling includes endogenous stratification, which means that frequent visitors are over-sampled compared to less frequent visitors. If the assumption of equidispersion (i.e., the same mean and variance) holds, the bias can be corrected by subtracting 1 from the number of visits using a standard Poisson regression (Shaw 1988). If overdispersion exists (i.e., the variance is greater than the mean), the negative binomial regression model can be used to accommodate the overdispersion parameter (Englin and Shonkwiler 1995; Martinez-Espineira and Amoako-Tuffour 2008).

In addition, the Poisson regression model and negative binomial regression model as zero-truncated count models have been applied to correct selection bias caused by non-zero and non-negative integer values of the number of visits as a dependent variable using on-site survey data (Shaw 1988; Creel and Loomis 1990; Grogger and Carson 1991; Gurmu 1991; Hellerstein and Mendelsohn 1993; Siderelis and Gustke 2000). The negative binomial regression model was found to be preferable if overdispersion was observed in the number of visits because the Poisson regression model assumes an equal mean and variance relationship (hereafter referred to as "equidispersion") (Gurmu 1991; Martinez-Espineira and Amoako-Tuffour 2008).

Despite the progress of the individual travel cost model in association with the three methodological challenges mentioned above, another methodological problem yet to be overcome is how to treat spatial interdependence among on-site survey respondents. Such spatial interdependence exists because of (1) information exchange, (2) locality of substitutes, and (3) preference sharing (Diamond 1980; Smirnov and Egan 2009). Exchange of information about a recreation site (e.g., word of mouth and small talk) may be a crucial part of the travel decision-making process since recreation choices made by visitors are shared with neighbors, resulting in spatially clustered trip patterns (Hushak 1975). Although information about public recreation sites such as forests or lakes can be relatively easily observed, spatial interdependencies between many private recreation facilities (e.g., a neighbor's pool that may be used by a survey respondent) are not. For this reason, the locality-of-substitute-amenity effect causes spatial interdependence.

It is natural that a peer effect of preference sharing on the travel decision-making process may exist because neighborhoods typically correlate with social status (Manski 2000; Scheinkman 2005). While some peer effect of preference sharing may be captured by including socioeconomic characteristics of the visitor's origin in the individual travel cost model, those that are not captured by the recording of socioeconomic characteristics (e.g., extended family, communal informal associations, and interest groups) can cause spatial interdependence (Diamond 1980). The failure to capture unobserved interactions possibly influencing spatial heterogeneity will cause a measurement errors relating to the distance measures.

Estimating the Individual Travel Cost Model

To achieve the objectives of this study, a recreation demand curve was estimated based on the individual travel cost model. *Ex ante* simulations of recreation demand were used to generate forecasts of the number of visits to the Forest for the purpose of comparing consumer welfare under *status quo* and hypothetically higher information satisfaction.

The dependent variable was the number of visits during the previous 12 months for individuals or groups. The independent variables in the model (i.e., travel cost to the Allegheny National Forest, travel cost to the nearest other national park or forest, travel cost to the nearest state park or forest, travel cost to the nearest local park or forest, satisfaction with recreation information availability, type of site at which the respondent was interviewed, survey year, number of children accompanied by the respondent, and number of people accompanied by the respondent) were chosen based on the general guidance of the individual travel cost literature.

Based on the coefficient of this variable, the predicted number of visits was estimated; consumer welfare from visiting the Allegheny National Forest was then estimated. Round-trip travel costs to different substitutable parks or forests were used to represent prices for substitutes for the Allegheny National Forest (Englin and Cameron 1996). A dummy variable reflecting satisfaction with recreation information availability was included in the model to test the hypothesis that higher satisfaction of recreation information availability—from “unsatisfied” to “satisfied”— increased the welfare of recreation site visitors (Lime and Stankey 1971; Reynolds and Braithwaite 2001; Mayes, Vogel and Lienemann 2004; LEES + Associates, Mustel Group and Urban Futures 2011).

Three other dummy variables indicating types of sites where respondents were interviewed (i.e., day-use developed sites, overnight-use developed sites, and wilderness) were included in the model. Since respondents were interviewed at four different forest site types, the three different dummy variables were included to differentiate experience in the forest. “General forest area” (GFA) was used as the reference (O'Neill and Davis 1991). One dummy variable indicating two survey years (i.e., 1 if surveyed in 2005, 0 if surveyed in 2001) was used to differentiate temporal differences in the number of visits. Variables relating to the number of people and number of accompanying children were added to differentiate individual or group characteristics (Caulkins, Bishop and Bouwes 1986).

Descriptions and detailed statistics for individual variables are reported in Table 10. The following four subsections describe how our model accommodated each of the four challenges.

Treating outliers

Since using a certain distance to judge outliers required an arbitrary cut-off value derived from *a priori* knowledge, conventional statistical approaches were utilized to detect outliers, i.e., "Cook's distance," "dfbeta," and the "hat matrix." Cook's distance is designed to assess the aggregate change in the parameter estimates by deleting observations (Cook 1977) while dfbeta assesses each change in the parameter estimates by deleting observations. The "hat matrix" measures how far an independent variable deviates from its mean based on the diagonal elements of the hat matrix, $h_i = \mathbf{x}_i'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{x}_i'$, where **x** is an $n \times (k+1)$ matrix representing explanatory variables, n is the number of observations, and k is the number of parameters in the model. Following conventional rules, the following were treated as potential outliers for the sensitivity test: (1) observations with a value of Cook's D greater than $4/n$, where n is the number of observations, (2) observations with a value of dfbeta greater than 1, and (3) observations with a value of the hat matrix greater than $2k/n$ (Bollen and Jackman 1990; Belsley, Kuh and Welsch 2004). In addition to the three samples from which potential outliers were removed, a sample with no exclusion of potential outliers was considered.

Substitute recreation sites

It was difficult to identify substitute sites in the NVUM data. For example, only 18 percent and 33 percent (128 and 256 out of 693 and 794) of the total number of respondents to the NVUM survey conducted in the Allegheny National Forest in 2001 and 2005 completed the answer to the questionnaire regarding substitute recreation sites (i.e., Have you been elsewhere for different activities during the past 12 months?). Such missing information leads to omitted variables representing the prices of substitute recreation sites. Thus, travel costs based on travel distances from a visitor's point of origin to the different levels of the nearest national park or forest, state park or forest, and local park or forest were used to represent the prices of substitute recreation sites.

On-site sample data

The probability distribution of the number of visits (Y_i) during the previous 12 months was specified using a negative binomial distribution:

$$(8) \qquad \Pr(Y = Y_i \mid \lambda, \alpha) = \frac{\Gamma(Y_i + 1/\alpha)}{Y_i!\Gamma(1/\alpha)} \left(\frac{1/\alpha}{1/\alpha + \lambda}\right)^{1/\alpha} \left(\frac{\lambda}{1/\alpha + \lambda}\right)^{Y_i},$$

where λ is the expected value of the distribution and α is the overdispersion parameter. When α is equal to 0, the negative binomial distribution is the same as a Poisson distribution $(\Pr(Y = Y_i \mid \lambda) = e^{-\lambda}\lambda^{Y_i} / Y_i!)$. To examine whether more-frequent visitors were sampled more than less-frequent visitors, the observed distribution of the number of visits was compared to the Poisson distribution and negative binomial distribution based on the same mean and variance. This comparison also helped identify the existence of overdispersion and the overdispersion parameter (α) will be tested if it is significantly different from 0 additionally.

Because Y_i was truncated at zero due to on-site sampling, the density of the negative binomial distribution was defined as:

$$(9) \qquad \Pr(Y = Y_i \mid Y > 0) = \frac{\Gamma(Y_i + 1/\alpha)}{\Gamma(Y_i + 1)\Gamma(1/\alpha)} (\alpha\mu)^{Y_i} (1 + \alpha\mu)^{-(Y_i + 1/\alpha)} \left(\frac{1}{1 - (1 + \alpha\mu)^{-1/\alpha}}\right).$$

where μ is the mean, which is called the rate or intensity parameter.

Treating spatial interdependence

Using Lambert and McNamara's (2009) notation, given the consistent estimator of equation (9), the error terms were assumed to be correlated between cross-sectional units (i.e., n locations of visitors) by an $n \times n$ nonstochastic matrix (**R**) with unknown elements whose row and column sums were uniformly bounded in absolute value:

(10) $u_{ij} = \mathbf{r}_j \varepsilon,\ \ \varepsilon \sim iid(0, \sigma^2)$,

where $\mathbf{r}_j$ is the jth row of matrix **R**. In spite of the unspecified form of **R**, Kelejian and Prucha (2007) suggested a consistent non-parametric estimator of the asymptotic distribution of the nonstochastic location determinant ($\mathbf{\Psi = X'\Sigma X}$, where non-diagonal spatial variance-covariance matrix $\mathbf{\Sigma} = E[\mathbf{uu'}]$). Since the asymptotic results extend to nonlinear models, including a variety of distributions, a spatial heteroskedastic autocorrelation consistent (HAC) estimator was applied to the negative binomial estimation model. The SAS code for this procedure is online available as data appendix in Lambert and McNamara (2009). The spatial HAC was applied for bivariate probit regression and spatial clustering methods to attend potential spatial error dependence (Stewart and Lambert 2011).

Covariance among the observations was modeled using a kernel density function, which decreases the influence of spatial interdependence among visitors as they live farther away from each other to adjust for covariance between visitors in different locations. A kernel function defines the extent where spatial autocorrelation exists among observations. Two types of sensitive tests for selecting kernel functions and bandwidths were conducted. While using different types of kernel is known to have little effect on the standard errors (Lambert et al. 2007; Anselin and Lozano-Gracia 2009), Parzen, Epanechnikov, Bartlett, and bi-square kernels (Cameron and Trivedi 2005) were applied to check the sensitivity of the results, i.e., the variations of standard errors with different kernels. Because the bandwidth selection may have additional influence on statistical inference (Cameron and Trivedi 2005), bandwidths with $n^{1/4}$, $n^{1/3}$, and $n^{1/2}$ cutoff values were used as another sensitivity test. More details about the spatial HAC estimator associated with kernel functions and bandwidth selection are available in Kelejian and Prucha (2007) and Lambert and McNamara (2009).

Ex ante simulation for annual per capita welfare

Following Englin and Shonkwiler (1995), Martinez-Espineira and Amoako-Tuffour (2008), and Heberling and Templeton (2009), individual annual per capita consumer welfare ($CS_i/person/year$) was calculated as [16]:

$$(11) \qquad CS_i \,/\, person \,/\, year = \hat{Y}_i \times \frac{(-1/\beta_{travel\,cost})}{NP_i},$$

where $\beta_{travel\,cost}$ is the coefficient of travel cost, $\hat{Y}_i$ is the predicted number of visits for observation i, and NP_i is the number of people in observation i.

Average annual per capita consumer welfare (i.e., $CS \,/\, person \,/\, year$) was calculated as:

$$(12) \qquad CS \,/\, person \,/\, year = \sum\nolimits_{i=1}^{N} \hat{Y}_i \times \frac{(-1/\beta_{travel\,cost})}{NP_i} \times \frac{1}{N},$$

where N is the number of observations. The predicted number of visits under the current level of satisfaction of recreation information availability (*status quo*) $(\hat{Y}_i)$ is replaced by the predicted

[16] Mathematical derivation from the negative binomial truncated link function to the consumer surplus estimator will be provided upon request.

number of visits under a hypothetically higher satisfaction of recreation information availability ($\hat{Y}_{i,hypothetical}$)to calculate the increase in average annual per capita consumer welfare.

(13) $$CS / person / year = \sum_{i=1}^{N} \hat{Y}_{i,hypothetical} \times \frac{(-1/\beta_{travel\,cost})}{NP_i} \times \frac{1}{N},$$

Empirical Results

Methodological challenges

The distribution of numbers of visits to the Allegheny National Forest was closer to the negative binomial distribution than to the Poisson distribution. The parameter of overdispersion (α) in equation (9) was statistically significant at the 5% level. While some deviations from the negative binomial distribution were observed, the deviation between the actual distribution and negative binomial distribution simulated at mean (λ) and overdispersion (α) parameters of 23.147 and 1.845 was not significant (P = 0.294, Kolmogorov-Smirnov test). This result implies no evidence of oversampling of frequent visitors, and thus endogenous stratification due to on-site sample data was not applicable to our dataset (Meisner, Wang and Laplante 2006).

The Cook's distance, dfbeta, and hat matrix approaches to the detection of outliers respectively identified 10, 1, and 23 observations as potential outliers. All coefficients, including the coefficient of travel cost to the Allegheny National Forest, were sensitive in terms of both magnitude and statistical significance to the different outlier detection approaches. For example, the coefficients for travel cost to the Allegheny National Forest were -0.004, -0.005, and -0.008 after removing observations detected as outliers by Cook's distance, dfbeta, and the hat matrix approaches, respectively. The inconsistency in the coefficients after the removal of potential outliers did not offer a clear view of which observations should be treated as outliers. In addition, many observations identified as potential outliers are not distant visitors, which implies that long-distance visits are not necessarily outliers.

Selections of kernel functions and bandwidth generated different standard error, but did not change the significance levels at the 5% when all observations were used. Given these results, regression results using a bi-square kernel with the K-nearest neighbor (KNN = $n^{1/2}$, where n = 347), without removing any observations as outliers, was used for the following discussion. For purposes of comparison, the sensitivity results using different conventional outlier detection methods and using different kernel functions and K-nearest neighbors are presented in the Appendix.

Parameter estimates

The travel cost to the Allegheny National Forest, the satisfaction of recreation information availability, site types (day-use developed sites, overnight-use developed sites, and wilderness), and the year of the survey were significant at the 5% level, while the number of children, the number of people, and travel cost to the nearest national parks or forests, travel cost to the nearest state parks or forests, and travel cost to the nearest local parks or forests were not significant at the 5% level (See Table 11). The negative sign of the travel cost to the Allegheny National Forest confirmed that recreation demand for the Allegheny National Forest follows the law of demand because the number of visits per year to the site (representing the quantity demanded) is inversely related to the price of using the Allegheny National Forest (represented by travel cost). The marginal effect of travel cost is –0.044, which suggested that an increase of \$10 in the travel cost per round trip to the Allegheny National Forest decreases the number of annual visits per group by 0.44 visits.

The marginal effect of the information satisfaction variable is positive and significant. This result indicates that visitors would increase the number of visits by about five times (4.777) per year if recreation information availability about the Allegheny National Forest increased from the "unsatisfactory" to the "satisfactory" level, *ceteris paribus*. The positive marginal effect of the information satisfaction variable on the number of visits implies that higher information satisfaction increases consumer welfare derived from use of the Allegheny National Forest. Thus, this finding suggests failure to reject the hypothesis—an increase in the satisfaction of recreation information availability (i.e., from unsatisfactory to satisfactory) increases the consumer welfare of recreation site visitors.

The significant marginal effects of the three site-type dummy variables suggest that the site type at which the respondents were interviewed affects the number of visits. Specifically, the marginal effects are -8.420, -11.168, and -8.434, indicating that the number of annual visits decreased by 8.420, 11.168 and 8.434 times if the survey was conducted at day-use developed sites, overnight-use sites and wilderness sites, compared to the number of visits to the general forest area. A positive and significant marginal effect for the year dummy variable suggests that per group visits in 2005 were 1.351 times higher than those in 2001.

The travel cost to the nearest other park or forest did not have significant marginal effects. This result suggests a lower level of substitutability with the Allegheny National Forest for other nearby parks or forests and implies the Allegheny National Forest as a recreation site possesses a uniqueness that is not available in other nearby parks or forests (USDA Forest Service 2011). For example, the Tionesta scenic area in the Allegheny National Forest provides the largest remaining old-growth forested area in Pennsylvania.

Consumer welfare

The number of visits to the Allegheny National Forest at the *status quo* level of information satisfaction was predicted to be 17.18 visits per year for 347 survey respondents. The corresponding consumer welfare was estimated to be $1,367,180 per year ($2,292 per capita per year). The number of visits to the Allegheny National Forest at the hypothetically satisfactory level of recreation information for the 347 respondents was predicted to be 18.70 visits per year. Under the hypothetically “satisfactory” level, the corresponding consumer welfare was estimated to be $1,488,283 per year ($2,497 per capita per year). Thus, the increased consumer welfare due to the improved satisfactory level of recreation information was estimated to be $120,103 ($205 per capita per year). This result was consistent with the estimated parameters from all models, as may be seen in the Appendix.

Conclusion

This research analyzed the change in consumer welfare due to the higher satisfaction of recreation information availability determined by on-site sample data collected from the Allegheny National Forest as a part of the National Visitor Use Survey project (NVUM 2003). The results show that the satisfaction of recreation information availability has a positive effect on the number of visit to a site, which generates higher annual per capita consumer welfare.

By addressing well-known methodological challenges associated with the individual travel cost model using on-site sample data (i.e., treatment of outliers, substitute recreation sites, and on-site sample data) and considering a relatively new methodological problem (i.e., treatment of measurement error due to spatial interdependence), *ex ante* simulations generated forecasts of the number of visits at the hypothetically “satisfactory” level of recreation information availability and at the *status quo* level of recreation information availability. To the best of our knowledge, potentially inconsistent standard error in the individual travel cost model has not been attempted to correct. Correcting the standard error using the spatial HAC estimator modifying SAS code obviated the possibility of inaccurate statistical inference due to spatial interdependence in the travel cost model.

Our finding of increase in average annual per capita consumer welfare among visitors due to higher information satisfaction can be used by recreation site managers in making budget decisions regarding improvements in recreation information. For example, assessing the increased recreation demand of a given site and the resulting level of consumer welfare improvement could be useful to recreation managers trying to justify budgeting for recreation information in increasingly tight financial situations. It is worth to note that such budgeting decision has to be under the assumption that providing quality information about recreational activities increases visitor satisfaction and the budget is allocated for creating quality recreational information.

Challenges remain. First, the opportunity cost of travel to the site was not considered, because income information was not available from survey respondents. Second, the lowest rate among the applicable IRS standard miles rates was used because exact travel costs were not available in the data. These two limitations suggest that the results reported in this study should be considered conservative estimates. Third, consumer welfare was calculated based on a travel cost model estimated with all observations because conventional statistical approaches failed to distinguish among models with and without potential multi-destination trips that are normally treated as outliers. This inability to identify potential outliers may have exaggerated consumer welfare estimates since inclusion of multi-destination trips may have overstated consumers' willingness to visit the Allegheny National Forest.

Table 10. Variable Names, Definitions, and Descriptive Statistics

Variable	Description	Mean	Std. Dev.	Min	Max
Number of visit	Number of visits during the previous 12 months for individuals or groups	23.147	55.479	1	365
Travel cost (TC) to ANF	Travel cost for round trip ($) to the Allegheny National Forest (ANF)	29.494	70.031	0.130	730.830
TC to national park or forest	Travel cost for round trip ($) to nearest other national park or forest	170.591	70.112	9.380	329.560
TC to state park or forest	Travel cost for round trip ($) to state park or forest	29.609	15.899	0.000	76.720
TC to local park or forest	Travel cost for round trip ($) to local park or forest	57.659	39.902	0.700	170.380
Information availability	Satisfaction about recreation information availability (1 if satisfied, 0 otherwise)	0.784	0.412	0	1
Day-use developed sites (DUDS)	Type of site at which the respondent was interviewed (1 if interviewed at day-use developed sites, 0 otherwise)	0.490	0.501	0	1
Overnight-use developed sites (OUDS)	Type of site at which the respondent was interviewed (1 if interviewed at overnight-use developed sites, 0 otherwise)	0.202	0.402	0	1
Wilderness (WILD)	Type of site at which the respondent was interviewed (1 if interviewed at wilderness, 0 otherwise)	0.046	0.210	0	1
Survey round	Dummy variable indicating survey year (1 if surveyed in 2005, 0 if surveyed in 2001)	0.617	0.487	0	1
Number of children	Number of accompanying children under 16 year–old	0.683	1.101	0	5
Number of people	Number of accompanying people in the same vehicle	2.666	1.370	1	8

Table 11. Estimation Result using a Spatially Heteroskedastic Autocorrelation Consistent Estimator (HAC) to a Zero Truncated Negative Binomial Regression (N=347, Epanechinikov, KNN 19).

Variable	Coefficient	Standard Error
Travel cost (TC) to ANF	-0.004*	0.001
TC to national park or forest	0.004	0.004
TC to state park or forest	0.003	0.003
TC to local park or forest	0.010	0.006
Information availability	0.547*	0.135
Day-use developed sites	-0.820*	0.152
Overnight-use developed sites	-1.614*	0.154
Wilderness	-1.519*	0.288
Survey round	0.136*	0.013
Number of children	-0.196	0.157
Number of people	-0.014	0.110
Intercept	1.506	0.439

* indicate statistical significance at the level of 5%.

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Appendix

Appendix table 1. Regressions results after removing observations detected as outliers by Cook's distance, dfbeta, and hat matrix (Epanechnikov kernel function and $n^{1/2}$ cutoff value).

Variable	Number of observations (N)			
	N=347	N=337 (Cook's D)	N=346 (dfbeta)	N=324 (hat matrix)
	Coefficient (Standard error)	Coefficient (Standard error)	Coefficient (Standard error)	Coefficient (Standard error)
Travel cost (TC) to ANF	-0.004* (0.001)	-0.004* (0.001)	-0.005* (0.001)	-0.008 (0.010)
TC to national park or forest	0.004 (0.004)	0.002 (0.003)	0.004 (0.003)	0.005 (0.078)
TC to state park or forest	0.003 (0.003)	-0.001 (0.003)	0.005 (0.003)	0.003 (0.008)
TC to local park or forest	0.010 (0.006)	0.005 (0.005)	0.007 (0.006)	0.007 (0.015)
Information availability	0.547* (0.135)	0.445* (0.123)	0.831* (0.160)	0.522 (0.325)
Day-use developed sites	-0.820* (0.152)	-0.576* (0.167)	-0.521* (0.131)	-0.825* (0.179)
Overnight-use developed sites	-1.614* (0.154)	-0.944* (0.172)	-1.305* (0.186)	-1.648* (0.738)
Wilderness	-1.519* (0.288)	-1.026* (0.297)	-1.286* (0.302)	-1.170 (1.467)
Survey round	0.136* (0.013)	-0.217 (0.117)	0.070 (0.060)	0.160 (0.328)
Number of children	-0.196 (0.157)	-0.062 (0.086)	-0.066 (0.128)	-0.146 (0.947)
Number of people	-0.014 (0.010)	-0.210* (0.076)	-0.226* (0.106)	-0.062 (1.804)
Intercept	1.506* (0.439)	2.517* (0.335)	1.639* (0.398)	1.673 (1.102)

* indicate statistical significance at the level of 5%.

Appendix table 2. Regressions results using different kernel functions (N=347, $n^{1/2}$ cutoff values).

Variable	Kernel function			
	Parzen	Epanechnikov	Bartlett	Bi-square
	Coefficient (Standard error)	Coefficient (Standard error)	Coefficient (Standard error)	Coefficient (Standard error)
Travel cost (TC) to ANF	-0.004* (0.001)	-0.004* (0.001)	-0.004* (0.001)	-0.004* (0.001)
TC to national park or forest	0.004 (0.005)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)
TC to state park or forest	0.003 (0.004)	0.003 (0.003)	0.003 (0.003)	0.003 (0.003)
TC to local park or forest	0.010 (0.010)	0.010 (0.006)	0.010 (0.007)	0.010 (0.007)
Information availability	0.547* (0.195)	0.547* (0.135)	0.547* (0.159)	0.547* (0.153)
Day-use developed sites	-0.820* (0.169)	-0.820* (0.152)	-0.820* (0.173)	-0.820* (0.173)
Overnight-use developed sites	-1.614* (0.165)	-1.614* (0.154)	-1.614* (0.169)	-1.614* (0.172)
Wilderness	-1.519* (0.358)	-1.519* (0.288)	-1.519* (0.336)	-1.519* (0.334)
Survey round	0.136* (0.035)	0.136* (0.013)	0.136* (0.001)	0.136* (0.006)
Number of children	-0.196 (0.206)	-0.196 (0.157)	-0.196 (0.181)	-0.196 (0.180)
Number of people	-0.014 (0.144)	-0.014 (0.100)	-0.014 (0.125)	-0.014 (0.125)
Intercept	1.506* (0.559)	1.506* (0.439)	1.506* (0.519)	1.506* (0.521)

* indicate statistical significance at the level of 5%.

Appendix table 3. Regressions results using different bandwidth selection (N=347, Epanechinikov).

Variable	Bandwidth cutoff value		
	KNN 4 (= $n^{1/4}$)	KNN 7 (= $n^{1/3}$)	KNN 19 (= $n^{1/2}$)
	Coefficient (Standard error)	Coefficient (Standard error)	Coefficient (Standard error)
Travel cost (TC) to ANF	-0.004* (0.001)	-0.004* (0.001)	-0.004* (0.001)
TC to national park or forest	0.004 (0.003)	0.004 (0.003)	0.004 (0.004)
TC to state park or forest	0.003 (0.003)	0.003 (0.004)	0.003 (0.003)
TC to local park or forest	0.010* (0.004)	0.010 (0.005)	0.010 (0.006)
Information availability	0.547* (0.118)	0.547* (0.126)	0.547* (0.135)
Day-use developed sites	-0.820* (0.123)	-0.820* (0.132)	-0.820* (0.152)
Overnight-use developed sites	-1.614* (0.133)	-1.614* (0.152)	-1.614* (0.154)
Wilderness	-1.519* (0.304)	-1.519* (0.297)	-1.519* (0.288)
Survey round	0.136 (0.098)	0.136 (0.110)	0.136* (0.013)
Number of children	-0.196* (0.088)	-0.196 (0.107)	-0.196 (0.157)
Number of people	-0.014 (0.064)	-0.014 (0.068)	-0.014 (0.110)
Intercept	1.506* (0.421)	1.506* (0.429)	1.506 (0.439)

* indicate statistical significance at the level of 5%.

VITA

Seung Gyu Kim was born in Korea on March 14, 1977. He graduated in February of 2003 from Korea University, Seoul, Korea, with a B.A. in Economics from the Department of Food and Resource Economics. In August of 2005, he entered the graduate programs in the Department of Agricultural and Resource Economics at the University of Tennessee, Knoxville. In August of 2007, he was granted his M.S. in Agricultural Economics. In August of 2011, he was awarded his Ph.D. in Natural Resources, Natural Resource Economics Concentration.