Spatial Fragmentation and the Value of Residential Housing

Todd H. Kuethe

ABSTRACT. *This study examines the impacts of spatial fragmentation and land use diversity on single-family residential real estate values. Through hedonic price analysis, we estimate the implicit price effects of spatial fragmentation and neighborhood land use diversity in the city of Milwaukee, Wisconsin. Spatial econometric estimates suggest that house prices are negatively impacted by spatial fragmentation at low levels of fragmentation, yet there is a positive price relationship at high levels of fragmentation. The results also suggest that house prices do not share a statistically significant relationship with land use diversity.* (JEL R14, R21)

I. INTRODUCTION

Lancaster's (1966) theory of consumer demand posits that the market value of a good is determined by the value of its characteristics. Real estate differs from many other goods because, by definition, it is tied to a particular location, and as a result, many of its characteristics are shaped by the surrounding physical environment. This notion has motivated a substantial body of research that addresses the price impact of various land use activities on neighboring properties. The majority of the existing studies focus on the impact of a single activity of interest; recent examples include oil and natural gas facilities (Boxall, Chan, and McMillan 2005), airports (Cohen and Coughlin 2008), and urban green space (Conway et al. 2009). However, a more recent stream of literature suggests real estate values are determined by a more complex process. Munroe (2007), for one, demonstrates that land markets reflect a variety of spatial factors that collectively influence real estate values. The complexity of a physical environment has been incorporated into the modeling practices of other disciplines, such as ecology and geography, and Geoghegan, Wainger, and Bockstael (1997) suggest that models of real estate values should similarly account for the arrangement of a number of land use activities in the determination of housing values.

This paper explores the growing concerns of the arrangement of multiple land use activities within a physical environment and seeks to identify the price impacts of the fragmentation of land use activities. Fragmentation, in its simplest form, relates to the discontinuities between subgroups within some larger population. The study of fragmentation crosses a number of disciplines, such as urban planning and design, ecology, and regional economics.

As it relates to each discipline, fragmentation carries several meanings. Altinok and Cengiz (2008) define four forms of land use fragmentation. First, fragmentation has been examined from an ecological or environmental perspective. *Ecological fragmentation* addresses such topics as maintaining biodiversity and preserving natural landscapes. Ecological fragmentation can arise from natural processes that alter the layout of the physical environment of a landscape, or by human activity. Second, *political fragmentation* addresses the division of a landscape into multiple political units. High degrees of political fragmentation are associated with the division of an area into numerous administrative units with little collaboration among them. Political fragmentation plays an important role in fostering economic growth and land use patterns, yet increased political fragmentation may also foster urban sprawl, which carries a number of negative external-

Land Economics • February 2012 • 88 (1): 16–27
ISSN 0023-7639; E-ISSN 1543-8325

The author is an economist, Economic Research Service, U.S. Department of Agriculture, Washington, D.C.

ities (Ulfarsson and Carruthers 2006; Razin and Rosentraub 2000). Third, fragmentation has also been examined through a behavioral perspective, called *social fragmentation*. A population with a high degree of social fragmentation is characterized by limited connections between subgroups, such as groups formed by common culture, language, race, or income level. For example, Coy (2006) highlights the disamenities associated with social fragmentation in Latin America. In this case, social fragmentation is the result of the development of gated communities, which lead to increased levels of economic disparity and social inequality. *Spatial fragmentation*, on the other hand, addresses the discordance of land use activities and the physical properties of space. A highly spatially fragmented landscape is divided into several small areas (or fragments) each with a distinct land use activity. High spatial fragmentation is characterized by separation of land use activities, such as housing, businesses, recreation, and manufacturing, into separate and distinct areas.

Another important land use feature that is often studied in conjunction with fragmentation is land use diversity, or land use mix. Land use diversity addresses the arrangement of fragmented land use activities. A diverse landscape includes a mix of several neighboring land use activities. For example, a well-diversified neighborhood may contain a mix of commercial, residential, and open-space fragments. Geoghegan, Wainger, and Bockstael (1997) highlight the relationship between land use diversity and spatial fragmentation and provide some notion of the potential effects of each. The authors suggest that increasing diversity might lower property values by introducing negative visual and noise externalities, yet diversity may also provide convenient access to work, shopping, and recreational activities. On the other hand, increased fragmentation may indicate a more checkered landscape with potentially conflicting neighboring land use activities.

Although fragmentation and diversity are often studied jointly, as by Geoghegan, Wainger, and Bockstael (1997), the two phenomena are not always in concert. Fragmentation addresses the atomization of land use activities, and diversity addresses the variegation of land use activities within a given location. A landscape may be highly fragmented but not diverse if it is marked by several small patches of a single land use activity. For example, a residential neighborhood may be divided into several small blocks occupied solely by single-family residential units. Alternatively, a location may have a low degree of fragmentation (large land use patches or areas) but high degree of diversity (several categories of land use activities within the neighborhood).

This study addresses how spatial fragmentation and land use diversity may impact residential real estate values. Like other nonmarket goods, spatial fragmentation is associated with a number of amenities and disamenities that may be reflected in the value of residential properties. Previous studies suggest that fragmentation is associated with the following disamenities: excessive commute times, traffic congestion, air pollution, inefficient energy consumption, loss of open space and habitat, inequitable distribution of economic resources, job-housing imbalance, and loss of sense of community (Song and Knaap 2004). Similarly, Song and Knaap (2004, 664) state that increasing land use diversity can "promote transit-supportive development, preserve open space and other landscape amenities, facilitate a more economic arrangement of land uses, encourage street activity to support retail businesses, help achieve regional housing and employment targets, reinforce streets as public spaces, encourage pedestrian and bicycle travel, and thereby create a sense of community."

The implicit price effects are estimated through hedonic price analysis. Although hedonic analysis has long been used to examine the price effects of specific land use activities, there has been little empirical work that directly addresses spatial fragmentation and land use diversity. Exceptions include work by Song and Knaap (2004), who find a negative price relationship between land use diversity and housing values in Washington County, Oregon. Kockelman (1997) examined both housing values and rents in San Francisco, California, and finds a statistically significant and negative relationship between property values and spatial fragmentation. The results, however, do not suggest a meaningful relationship between values and land use diversity. Geoghegan, Wainger, and Bockstael (1997) find that increased land use diversity is associated with higher house prices in several suburbs of Washington, D.C. The same study indicates that spatial fragmentation, on the other hand, does not impact housing values.

Given the ambiguity of previous conclusions, this study seeks to provide further insight into the role of spatial fragmentation and land use diversity in the determination of residential property values. This study contributes to the existing literature by estimating the price impacts of fragmentation and diversity in the small midwestern city of Milwaukee, Wisconsin. The area is a quite different from the large metropolitan areas examined in similar studies, such as Washington, D.C. (Geoghegan, Wainger, and Bockstael 1997); San Francisco, California (Kockelman 1997); and Washington County, Oregon, which borders Portland (Song and Knaap 2004). The choice of study area may reveal whether or not the previous conclusions hold for smaller, industrial cities. Further, the analysis examines a dataset that is freely available through the World Wide Web, and the results may, therefore, be easily replicated or expanded in future research. Finally, the study draws conclusions based on modern spatial econometric methods that were not widely adopted at the time of the previous studies. The spatial econometric methods control for spatial effects inherent in real estate transaction and land use data, and numerous studies demonstrate the advantages of spatial econometric techniques in modeling the determination of real estate values.

II. THE HEDONIC PRICE METHOD

The hedonic price method is a market clearing function that defines an equilibrium after all interactions between supply and demand have taken place. The market clearing function can be expressed in a single equation in which the market value of a good is a function of the value of its characteristics (Rosen 1974). The hedonic price function for house i is defined as

$$P_i = f(S_i, E_i, L_i), \qquad [1]$$

where P_i is the market value of house i, S_i is a set of structural characteristics, E_i is a set of environmental characteristics, and L_i is a set of locational characteristics for each house i. Empirically, the underlying market value of each characteristic can be identified through regression analysis. Drawing from [1], the regression equation takes the form

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \varepsilon, \qquad [2]$$

where $\mathbf{y}$ is an $N \times 1$ vector of observed house prices or assessed values. The matrix $\mathbf{X}$ contains the K quantifiable characteristics of each house, with dimensions $N \times K$. The contribution of each attribute to the value of a home is captured by a set of unknown parameters $\boldsymbol{\beta}$, a $K \times 1$ vector. Following standard regression procedures, the disturbance term is typically assumed to follow a white noise process with mean zero and constant variance, $\varepsilon \sim N(0,\sigma^2)$. Thus, an inherently linear hedonic price function can be easily estimated by least squares.

III. DATA

To estimate the price effects of spatial fragmentation on residential real estate prices, our model employs data from the 2005 single-family residential real estate transaction record for the city of Milwaukee, Wisconsin, obtained from the city of Milwaukee assessor's office (City of Milwaukee 2009). The data are freely available in electronic format through the World Wide Web. Milwaukee is an attractive area for analysis because, in many ways, it is representative of older American industrial cities (McMillen 2001). Milwaukee is one of the hubs of economic activity in the Upper Midwest section of the United States. Milwaukee is the largest city in the state of Wisconsin and serves as the seat of Milwaukee County. The city spans 96 square miles of southeastern Wisconsin, with a population density of 6,214 persons per square mile (U.S. Census Bureau 2000). After cleaning the data, the record yields 5,976 transactions that include the sales price and a number of characteristics of each home for use as explanatory variables in the hedonic price model. In addition, a number of location

TABLE 1
2005 Transaction and Land Use Data Summary Statistics

Variable	Mean	Std. Dev.
Sales price (dollars)	131,874.000	69,608.100
Bedrooms	3.608	1.231
Full bathrooms	1.484	0.596
Half bathrooms	0.259	0.502
Age (years)	6.062	2.209
Lot size (acres)	0.125	0.058
Distance (miles)		
City center	4.427	2.018
Commercial land use	0.106	0.082
Manufacturing land use	0.322	0.266
Open space	0.082	0.073
Transportation hub	0.197	0.155
Fragmentation	0.033	0.022
Land use diversity	1.364	0.272
Dummy (proportion, %)		
Basement	87	
Attic	40	
Fireplace	10	
Central air conditioning	31	
Attached garage	6	
Detached garage	62	

characteristics were identified through geographic information systems (GIS) analysis. Table 1 provides a summary of the data employed in the hedonic price model.

In 2005, the average sales price for a single-family home in Milwaukee was approximately $131,874. The mean values of the (continuous) structural characteristics are 3.6 bedrooms, 1.5 full bathrooms, and 0.3 half bathrooms. The average age is six years, and the average lot size is approximately 0.13 acres (5,662 square feet). A set of categorical variables was also created for additional structural characteristics, taking the value of one if the property includes the characteristic and zero otherwise. The proportion of homes taking the value of one for each characteristic is 87% for basement, 40% for attic, 10% for fireplace, 31% for central air-conditioning, 6% for attached garage, and 62% for detached garage. All of the structural characteristics are expected to exhibit positive effects on transaction prices at a statistically significant level.

The GIS locational variables measure the (linear) distance from a number of important land use activities. The classic model of urban form suggests that house prices decline as distance from the city center increases, so the distance from the city center is expected to have a negative impact on sales price (Alonso 1964). However, a number of studies argue that the traditional monocentric model does not accurately describe the spatial structure of most modern cities (McMillen 2006). In order to account for potential nonlinearities in the housing price gradient, our model also includes a squared distance term. The mean distance to the city center is approximately 4.43 miles. The other distance variables measure the distance from the nearest location of various land use activities, including commercial (0.11 miles), manufacturing (0.32 miles), open space (0.08 miles), and transportation hubs (0.20 miles). Manufacturing is expected to have a negative impact, and open space is believed to have a positive impact. The impact of commercial and transportation is not known a priori because each activity is associated with both positive and negative externalities. For example, transportation includes both easier access to the city center (positive) and increased noise levels (negative).

The measures of spatial fragmentation and diversity are calculated using a second dataset, which includes the complete property record for all parcels in the city of Milwaukee, the 2005 Master Property Record (MPROP) (City of Milwaukee 2007). The records are collected by the city of Milwaukee assessor's office and include all of the approximately 160,000 land parcels located within the city limits. The MPROP classifies all parcels into 13 general land use categories (Table 2). The land use classification system is used to identify properties for tax purposes, as well as zoning definitions. The classification system defines four separate residential land uses: single family, duplex, multifamily, and mixed commercial and residential uses. All commercial and industrial land uses are divided by industry, such as services, manufacturing, or agriculture. The remaining categories include all lands that are tax exempt, including public schools, churches, public parks, and vacant parcels. These categories, therefore, represent all of the potential land use alternatives for a given parcel. Table 2 also reports the number of patches and mean fragmentation (as measured by mean perimeter to area ratio, outlined below) for all land use classes

TABLE 2
2005 Land Use Classification and Summary Statistics

Land Use Activity	Count	Mean Perimeter/ Area Ratio
Residential		
Single family	19,287	0.035
Duplex	16,986	0.049
Multifamily	3,940	0.040
Mixed commercial and residential	2,274	0.050
Commercial		
Wholesale and retail trade	1,418	0.035
Services, finance, insurance, real estate	1,538	0.041
Mixed commercial	772	0.035
Manufacturing, construction, warehousing	815	0.032
Transportation	1,052	0.040
Agriculture, fishing	18	0.041
Public/quasi-public		
Public schools and buildings, churches, cemeteries, quasi-public buildings	1,965	0.032
Public parks, quasi-public open space	2,380	0.094
Vacant land	1,839	0.074

across the entire city of Milwaukee. It can be seen that single-family residential land use occupies the greatest number of patches, and public parks and quasi-public open space is the most fragmented land use activity.

The degree of spatial fragmentation and land use diversity for each neighborhood is calculated in three steps.[1]

1. The boundaries of parcels are "dissolved" by joining all neighboring parcels that belong to the same land use class. For example, if two congruent parcels are used for single-family residential purposes, the border between these two parcels is removed, and the result is one "patch" of single-family residential land.
2. Once each land use patch is identified, the area and perimeter of each patch is measured to calculate the perimeter to area ratio, a measure of spatial fragmentation. The ratio indicates whether fragments are small or spread out and was previously used by Geoghegan, Wainger, and Bockstael (1997).
3. The patch sizes are then used to calculate neighborhood-level measures of land use diversity.

To determine the economic value of fragmentation and diversity, the single-family residential land use patch statistics are then tied to each residential transaction and used as explanatory variables in the hedonic price model. Neighborhood-level land use diversity, based on the dissolved patch metrics across all 13 land use classes, is measured by Shannon's diversity index (SDI). Borrowing from the ecological literature, SDI is commonly used to measure the biodiversity of a landscape, where the measure tracks the abundance of various species in a given location (Krebs 1985, 1989). In a similar fashion, we calculate land use diversity using the equation

$$H = -\sum_{j=1}^{S} p_j \ln(p_j), \qquad [3]$$

where p_j is the relative occurrence of land use j, calculated as the proportion of patches of a given use to the total number of patches in the neighborhood, and S is the total number of land use classes (i.e., 13). The minimum value of SDI is zero when the neighborhood is dominated by a single patch, and SDI increases as the number of different land uses increases and/or the proportional distribution of area among patch types becomes more equitable (Krebs 1989). SDI has a maximum value of $\ln(S)$. Thus, for our analysis, the diversity of land use falls in the range $0 \leq H \leq 2.56$.

Although SDI has been used in a number of similar studies, there may be some dangers in using biological indices in economic applications. SDI assumes that each category represents a homogenous subgroup of the population of interest. In ecology, these sub-

[1] The measures were calculated using Patch Analyst software. Patch Analyst is an extension to the ArcGIS geographic information system suite that facilitates the spatial analysis of landscape patches (Rempel 2008). Patch Analyst is available as freeware. The extension is used for ecological spatial pattern analysis, often in support of habitat modeling, biodiversity conservation, and forest management. Ecological land use metrics have also been used in applied economics studies of land use by Parker and Meretsky (2004) and Irwin and Bockstael (2007). Geoghegan, Wainger, and Bockstael (1997) argue that the use of ecological landscape metrics in applied economics is a natural complement to ecology in that both humans and other animals have preferred habitats and are exposed to various land use amenities.

groups typically represent specific species, and the homogeneity assumption implies few limitations of interpretations. For example, a raccoon is a raccoon. This is not necessarily the case when studying land use activities where some heterogeneity within subgroups may exist. For example, the manufacturing classification does not inform to what degree plants emit pollution, which may vary across firms. However, the MPROP classification system parses the data into a greater number of categories than provided by similar previous studies (six categories for Song and Knaap [2004] and Kockelman [1997] and seven categories for Geoghegan, Wainger, and Bockstael [1997]). As a result, the potential heterogeneity within each land use category is expected to be lower when compared to existing studies.

Neighborhoods are defined by the Department of City Development, Neighborhood Identification Project (City of Milwaukee, Department of City Development 2000). The Neighborhood Identification Project was enacted in 2000 with the purpose of defining neighborhoods encompassing all of the residential areas of Milwaukee. The stated goal of the project is to define neighborhoods that remain stable over time for the purpose of collecting and comparing data. The factors considered by the Department of City Development to define neighborhoods include subdivisions, major streets, other physical and natural barriers, community group participation, housing styles, types, and ages, historic areas, and residents' opinions. The system includes a total of 190 neighborhoods, which range in size from 0.51 to 3.22 square miles with an average size of 0.51 square miles. The largest neighborhood accounts for 3.34% of the observation area.

Neighborhood land use diversity, as measured by SDI, is expected to have an impact on house prices for a number of reasons, yet the direction of the impact is not obvious a priori. It has been previously suggested that individuals not only value specific locational and environmental amenities, but they also value patterns of land use characterized by different housing densities, land uses, and open space (Geoghegan, Wainger, and Bockstael 1997). Existing studies of spatial fragmentation and property values suggest both positive (Geoghegan, Wainger, and Bockstael 1997) and negative effects (Kockelman 1997).

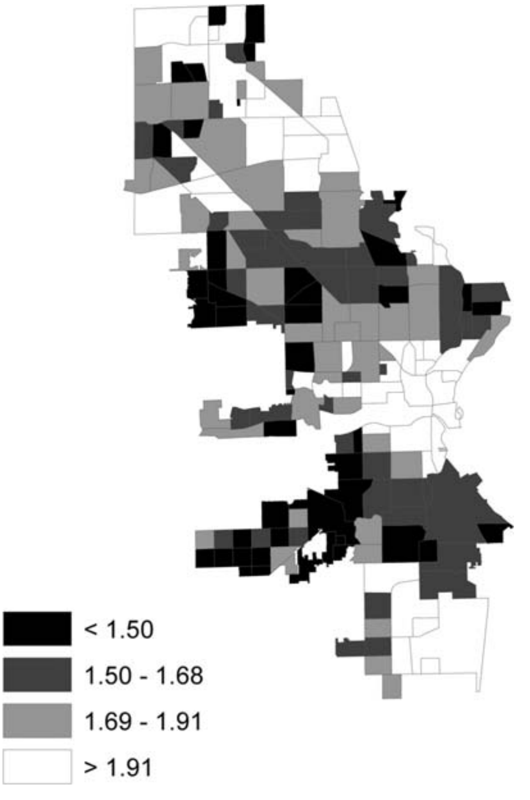

FIGURE 1
2005 Land Use Activity Diversity as Measured by the Shannon-Weiner Diversity Index by Neighborhood

Figure 1 shows the land use SDI results by neighborhoods. The SDI is divided into quartiles, with darker areas representing higher levels of diversity. The neighborhoods appear to exhibit a systematic pattern in which the least diverse neighborhoods are located at the city center and the outlying northern and southern portions of the city. The SDI ranges from zero, at the Lake Michigan waterfront, which is solely occupied by a public park, to 2.39 at the northern edge of downtown Milwaukee. The observed pattern of spatial fragmentation is consistent with previous research. Irwin and Bockstael (2007) find that diversity rises and then falls with distance from the city center.

As previously noted, spatial fragmentation does not necessarily imply land use diversity, nor does diversity imply fragmentation. The correlation between fragmentation and diversity for the data employed in the model is -0.14. Pearson's product-moment correlation test rejects a nonzero correlation between land use diversity and fragmentation. This suggests that neighborhood land use diversity and residential patch size are uncorrelated in our sample. Thus, as either fragmentation or diversity increases, it does imply a change in the other. In addition, the two measures do not introduce multicollinearity.

IV. ESTIMATION AND RESULTS

Although the hedonic price model has been traditionally estimated by ordinary least squares (OLS), spatial econometric estimation techniques have become increasingly popular. Spatial econometric methods provide a framework to address two important aspects of real estate transactions data: spatial dependence and spatial heterogeneity. Spatial dependence is a special case of cross-sectional dependence in which the structure of the covariation between observations at different locations is subject to spatial ordering, and spatial heterogeneity is a special form of structural instability in which the spatial structure of a process provides the basis of the specification of heterogeneity (Anselin 1988). The existing literature provides a number of examples of the causes of spatial dependence and heterogeneity in hedonic models, including similarity in structural characteristics (Basu and Thibodeau 1998), shared locational amenities (Gelfand et al. 1998), and the influence of real estate professionals (Bowen, Mikelbank, and Prestegaard 2001). Other studies have also shown that spatial effects can be the result of model misspecification (Anselin and Griffith 1988; Anselin et al. 1996; McMillen 2003). Spatial econometric methods have been used in a number of previous hedonic price studies; examples include the price impacts of wildfire risk (Donovan, Champ, and Butry 2007), residential community associations (Rogers 2006), and air quality (Kim, Phipps, and Anselin 2003). In addition, it has been shown that spatial econometric techniques generally outperform traditional hedonic price models when predicting real estate values (Kuethe 2011; Case et al. 2004).

The two most common spatial econometric specifications are the spatial lag and spatial error models. The spatial lag model captures spatial dependence in the regressant by including spatially weighted values of the dependent variable on the right-hand side of the equation (Anselin 1988). The spatial error model addresses the problems associated with spatially correlated omitted or unobserved variables, the effects of which are relegated to the error term (Anselin 1988).

The spatial lag model takes the form

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \varepsilon, \qquad [4]$$

where $\mathbf{W}$ is an $N \times N$ exogenous spatial weights matrix and ρ is an unknown scalar spatial parameter. The spatial weights matrix identifies the meaningful neighborhood for each observation. The off-diagonal elements take a value greater than zero when two observations share a meaningful relationship. Similarly, no observation can be a neighbor to itself, and as a result, the diagonal elements equal zero. The sign of the unknown parameter indicates the nature of the spatial dependence, such that a positive (negative) sign suggests the presence of positive (negative) spatial dependence in observed real estate values. The spatial lag term, $\mathbf{Wy}$, is endogenous, so OLS may lead to biased estimates of the regression coefficients. There are a number of alternative estimation procedures, such as maximum likelihood or two-stage least squares (Anselin 2006).

The spatial error model takes the form

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + u, \qquad [5a]$$

$$u = \lambda\mathbf{W}u + \varepsilon, \qquad [5b]$$

where u is a disturbance term that is assumed to follow a spatial autoregressive process. The process is a function of the unknown spatial parameter λ and an exogenous spatial weights matrix $\mathbf{W}$. Similar to the spatial lag coefficient, the sign of λ indicates the nature of the spatial dependence of the regression residuals. The remaining disturbance term ε is assumed to retain the standard properties and is assumed to be free of remaining spatial dependence. It can be seen that the error terms u are nonspherical, so the assumptions of OLS are violated. Alternative estimation procedures include maximum likelihood or general moments (GM) (Anselin 2006; Kelejian and Prucha 1999).

Typically, the preferred specification of the hedonic price model is selected using a set of specialized Lagrange multiplier tests and their robust equivalents developed by Anselin et al. (1996). However, a number of researchers also provide theoretical motivations for the spatial lag and error models. Patton and McErlean (2003) argue that ignoring spatial lag dependence carries severe consequences as a result of the potential bias of the aspatial form. However, Anselin and Lozano-Garcia (2009) argue that the spatial error specification provides a more natural fit to hedonic analysis as a result of the high potential for spatially related omitted or unobservable variables in real estate transaction data. Mueller and Loomis (2008) argue that the failure to account for either form of spatial relationships is detrimental because spatial lag dependence may lead to biased policy recommendations and spatial error dependence may lead to a failure to reject a policy relevant null hypothesis.

Theory provides little guidance in selecting the functional form of the hedonic price model, and the existing literature provides a number of alternatives (Green and Malpezzi 2003; Halvorsen and Pollakowski 1981; Rosen 1974). The most popular functional form, the semilog, follows the expression

$$\ln \mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \varepsilon, \quad [6]$$

where the value of each home is expressed in natural logs, and the regressors are expressed in levels. The functional form is computationally simple, and Follain and Malpezzi (1980) outline the benefits of the semilog specification. First, the marginal value of each characteristic varies so that the price of one characteristic depends, in part, on the house's other characteristics. A simple linear specification in which the regressant and the explanatory variables are expressed in levels assumes that the price impact of an additional bathroom is equal across all observations, say, for both three- and five-bedroom houses. The semilog model, on the other hand, allows the value added to vary proportionally with the size and quality of each home. This is best observed given the alternative expression $\mathbf{y} = e^{\mathbf{X}\boldsymbol{\beta}}$. Second, the coefficients of the semilog specification can be interpreted as "semielasticities." The coefficient estimates reflect the percent change in price given a *one unit* change in the value of the explanatory variable. It is important to note, however, that the semielasticities for dummy variables require some additional modification, as outlined by Halvorsen and Palmquist (1980). The semielasticity for a dummy variable is given by $\xi_d = e^{\boldsymbol{\beta}_d} - 1$ where $\boldsymbol{\beta}_d$ is the coefficient estimate for the dummy variable d.

The OLS estimates of the semilog hedonic price equation are presented in the first column of Table 3. All of the coefficients adhere to the expected sign, with exception of the distance to the nearest open space and the basement indicator variable. The open-space coefficient suggests that ceteris paribus, homeowners are willing to pay a premium to live farther from open space. Although the result is not consistent with a number of previous studies, it may be the result of the open-space definition provided by the city of Milwaukee, which includes public parks but also cemeteries and undeveloped vacant lands. The adjusted R^2 of 0.312 suggests that the model provides a reasonable fit.

Table 3 also includes the results of the spatial econometric specification tests. All of the spatial specification tests employ a row-normalized inverse-distance spatial weights matrix. This specification assumes that the value of each house is related to the price of all other observations, yet the influence declines as distance between observations increases. Thus, the matrix yields a distance-weighted "average" value in which nearer observations receive a greater weight. The Lagrange multiplier test statistics for both the spatial lag and spatial error models are statistically significant, as are their robust equiva-

TABLE 3
Hedonic Model Results

Variable[a]	Ordinary Least Squares Coef.	Ordinary Least Squares Std. Error	Spatial Error Coef.	Spatial Error Std. Error
Constant	11.162	0.074***	11.279	0.088***
Age	− 0.062	0.015***	− 0.065	0.012***
Age squared	0.001	0.001	0.001	0.001
Bedroom	0.027	0.006***	0.048	0.004***
Full bath	0.196	0.012***	0.128	0.009***
Half bath	0.166	0.013***	0.092	0.009***
Basement (d)	− 0.035	0.020*	0.019	0.015
Attic (d)	0.023	0.013*	− 0.002	0.010
Fireplace (d)	0.185	0.020***	0.087	0.015***
Air conditioning (d)	0.095	0.014***	0.014	0.010
Attached garage (d)	0.127	0.030***	0.048	0.022**
Detached garage (d)	0.095	0.015***	0.036	0.012***
Lot size	0.679	0.130***	0.489	0.103***
City center	0.022	0.017	0.068	0.031**
City center squared	− 0.004	0.001***	− 0.006	0.003**
Commercial use	0.412	0.080***	0.175	0.090**
Manufacturing use	0.086	0.026***	0.112	0.051**
Open space	1.339	0.087***	0.297	0.104***
Transportation	− 0.066	0.045	0.078	0.071
Fragmentation	− 2.361	3.042	− 7.453	2.240***
Fragmentation squared	4.857	18.549	42.405	13.477***
SI	0.048	0.022**	0.009	0.017
Adjusted R^2	0.3120			
Error	7,479.09***			
Lag	7,318.15***			
Robust error	612.29***			
Robust lag	451.35***			
Spatial error coefficient			0.717	

[a] "(d)" signifies the variable is a dummy, taking the value of 1 if true and 0 otherwise.
* Significant at $\alpha \leq 0.10$; ** significant at $\alpha \leq 0.05$; *** significant at $\alpha \leq 0.01$.

lents. This suggests that a spatial specification is preferred to the naive aspatial form. Anselin et al. (1996) suggest that when both of the specification tests are statistically significant, the test with the larger statistic value is preferred. As previously stated, the spatial error model mitigates the problems associated with spatially dependent omitted or unobservable variables. As a result, the hedonic price model is estimated following the spatial error specification using the Kelejian and Prucha (1999) GM estimator. The results of the spatial error estimation are presented in Column 2 of Table 3.

Most of the coefficient estimates of the spatial error specification are statistically significant. Exceptions include age squared (which suggests a linear price depreciation over time) and the structural characteristics for basement, attic, and air conditioning. In addition, the results suggest that house prices exhibit an inverse U-shaped relationship with respect to distance from the city center. The coefficient estimates show that house prices are expected to increase as one moves farther from the city center, yet prices decline beyond a distance of 5.67 miles. The results suggest a price premium for homes located farther from commercial and manufacturing land use activities. Again, the only coefficient that does not adhere to the expected sign is the open-space distance measure discussed previously. It should also be noted that the GM estimation procedure treats λ as a nuisance parameter, and its significance, therefore, cannot be addressed. However, the coefficient is positive, which suggests that the regression residuals are positively spatially correlated.

The variables of greatest interest to this study are the measures of spatial fragmentation and land use diversity. When comparing the results across the two estimation procedures, the coefficient estimates tell drastically different stories. The OLS estimation suggests that spatial fragmentation bears no significant effect on real estate values, and the results suggest that land use diversity is positively related to housing prices. The findings are consistent with those of Geoghegan, Wainger, and Bockstael (1997).

As previously noted, in the presence of spatial dependence, OLS estimates are suspect as a result of bias (spatial lag) or inefficiency (spatial error). As noted previously, the spatial specification tests suggest that the spatial error model is the preferred specification. The presence of spatial error dependence in the hedonic price model may lead to inefficient standard errors, and as a result, failure to account for the spatial error component may lead to the failure to reject policy relevant null hypothesis (Mueller and Loomis 2008). The spatial error estimation suggests that, in contrast to OLS, land use diversity does not share a meaningful relationship with house prices. Fragmentation, however, plays a statistically significant role in the determination of residential real estate values. The results are consistent with those of Kockelman (1997), who finds a similar positive relationship.

In contrast to previous studies, our hedonic price model includes a squared perimeter to area ratio variable to capture potential nonlinearities in the return to fragmentation. The coefficient estimates indicate the housing prices and spatial fragmentation share an inverse U-shape relationship. Housing values are expected to decline as spatial fragmentation increases until the perimeter to area ratio reaches a value of 5.68. However, this value is drastically higher than the mean ratio for single-family homes reported in Table 2. Therefore, one may conclude that homes within the sample are in the range in which housing values are expected to decline with increased fragmentation.

In sum, the results suggest that spatial fragmentation is negatively associated with housing prices, yet housing prices do not share a meaningful relationship with land use diversity. This implies that housing prices are expected to decline as neighborhoods grow more fragmented, or more specifically, if residential land use patch sizes decrease. This suggests that homeowners prefer to be located adjacent to other single-family residential parcels. The land use diversity finding suggests that mixed land use development may not be an appropriate policy or development goal with respect to increasing land values.

V. CONCLUSION

This study examines the economic value of spatial fragmentation and land use diversity through hedonic price analysis. The hedonic price model identifies the impacts of spatial fragmentation and land use diversity on the sales price of single-family houses in the city of Milwaukee, Wisconsin. The analysis suggests that housing values are negatively associated with spatial fragmentation at small levels of fragmentation, yet negative returns to size can be observed at high levels of spatial fragmentation. Land use diversity, on the other hand, does not appear to significantly impact residential housing prices.

The results offer potential avenues for future research. For example, the study may be extended to examine the relationship between house price appreciation and changing levels of spatial fragmentation over time. The temporal dynamics of spatial fragmentation, as they relate to urban sprawl, have been previously addressed by Irwin and Bockstael (2007). This study could, therefore, be extended to examine the spatial and temporal dynamics of changes in spatial fragmentation as they relate to land values through a panel data treatment of the current approach.

Acknowledgments

Disclaimer: The views expressed are those of the author and should not be attributed to ERS or USDA.

References

Alonso, William. 1964. *Location and Land Use*. Cambridge, MA: Harvard University Press.

Altinok, Emrah, and Hüseyin Cengiz. 2008. “The Effects of Urban Sprawl on Spatial Fragmentation and Social Segregation in Istanbul.” In *Proceed-*

ings of the 44thISOCARP Congress. The Hague: International Society of City and Regional Planners.

Anselin, Luc. 1988. *Spatial Econometrics: Methods and Models.* Dordrecht: Kluwer Academic Publishers.

———. 2006. "Spatial Econometrics." In *Palgrave Handbook on Econometrics: Volume I, Econometric Theory,* ed. Terence C. Mills and Kerry Patterson. Houndmills, Basingstoke, Hampshire, UK: Palgrave McMillan.

Anselin, Luc, Anil K. Bera, Raymond Florax, and Mann J. Yoon. 1996. "Simple Diagnostic Tests for Spatial Dependence." *Regional Science and Urban Economics* 26 (1): 77–104.

Anselin, Luc, and Daniel A. Griffith. 1988. "Do Spatial Effects Really Matter in Regression Analysis?" *Papers in Regional Science* 65 (1): 11–34.

Anselin, Luc, and Nancy Lozano-Gracia. 2009. "Spatial Hedonic Models." In *Palgrave Handbook of Econometrics: Volume II, Applied Econometrics,* ed. Terence C. Mills and Kerry Patterson. Houndmills, Basingstoke, Hampshire, UK: Palgrave McMillan.

Basu, Sabyasachi, and Thomas G. Thibodeau. 1998. "Analysis of Spatial Autocorrelation in House Prices." *Journal of Real Estate Finance and Economics* 17 (1): 61–85.

Bowen, William M., Brian A. Mikelbank, and Dean M. Prestegaard. 2001. "Theoretical and Empirical Considerations Regarding Space and Hedonic Housing Price Model Applications." *Growth and Change* 32 (4): 466–90.

Boxall, Peter C., Wing Chan, and Melville L. McMillan. 2005. "The Impact of Oil and Natural Gas Facilities on Rural Residential Property Values: A Spatial Hedonic Analysis." *Resource and Energy Economics* 27 (3): 248–69.

Case, Bradford, John Clapp, Robin Dubin, and Mauricio Rodriguez. 2004. "Modeling Spatial and Temporal House Price Patterns: A Comparison of Four Models." *Journal of Real Estate Finance and Economics* 29 (2): 167–91.

City of Milwaukee. 2007. *Master Property Record.* Available at www.city.milwaukee.gov/DownloadTabularData3496.htm (accessed March 23, 2010).

———. 2009. *Ownership, Assessment, and Sales Data.* Available at http://assessments.milwaukee.gov/mainsales.html (accessed March 23, 2010).

City of Milwaukee, Department of City Development. 2000. *Milwaukee Neighborhood Identification Project.* www.milwaukee.gov/ImageLibrary/Public/map4.pdf (accessed March 23, 2010).

Cohen, Jeffrey P., and Cletus C. Coughlin. 2008. "Spatial Hedonic Models of Airport Noise, Proximity, and Housing Prices." *Journal of Regional Science* 48 (5): 859–78.

Conway, Delores, Christina Li, Jennifer Wolch, Christopher Kahle, and Michael Jerrett. 2009. "A Spatial Autocorrelation Approach for Examining the Effects of Urban Greenspace on Residential Property Values." *Journal of Real Estate Finance and Economics* 41 (2): 1–20.

Coy, Martin. 2006. "Gated Communities and Urban Fragmentation in Latin America: The Brazilian Experience." *GeoJournal* 66 (1–2): 121–32.

Donovan, Geoffrey H., Patricia A. Champ, and David T. Butry. 2007. "Wildfire Risk and Housing Prices: A Case Study from Colorado Springs." *Land Economics* 83 (2): 217–33.

Follain, James R. and Stephen Malpezzi. 1980. *Dissecting Housing Value and Rent.* Washington, DC: Urban Institute Press.

Gelfand, Alan E., Sujit K. Ghosh, John R. Knight, and C. F. Sirmans. 1998. "Spatio-Temporal Modeling of Residential Sales Data." *Journal of Business and Economic Statistics* 16 (3): 312–21.

Geoghegan, Jacqueline, Lisa A. Wainger, and Nancy E. Bockstael. 1997. "Spatial Landscape Indices in a Hedonic Framework: An Ecological Economics Analysis Using GIS." *Ecological Economics* 23 (3): 251–64.

Green, Richard K. and Stephen Malpezzi. 2003. *A Primer on U.S. Housing Markets and Housing Policy*. Washington, DC: Urban Institute Press.

Halvorsen, Robert, and Raymond Palmquist. 1980. "The Interpretation of Dummy Variables in Semilogarithmic Equations." *American Economic Review* 70 (3): 474–75.

Halvorson, Robert, and Henry O. Pollakowski. 1981. "Choice of Functional Form for Hedonic Price Equations." *Journal of Urban Economics* 10 (1): 37–49.

Irwin, Elena G. and Nancy E. Bockstael. 2007. "The Evolution of Urban Sprawl: Evidence of Spatial Heterogeneity and Increasing Land Fragmentation." *Proceeding of the National Academy of Sciences* 104 (52): 20,67277.

Kelejian, Harry H. and Ingmar R. Prucha. 1999. "A Generalized Moments Estimator for the Autoregressive Parameter in a Spatial Model." *International Economic Review* 40 (2): 509–33.

Kim, Chong W., Tim Phipps, and Luc Anselin. 2003. "Measuring the Benefits of Air Quality Improvement: A Spatial Hedonic Analysis." *Journal of Environmental Economics and Management* 45 (1): 24–39.

Kockelman, Kara M. 1997. "Effects of Location Elements on Home Purchase Prices and Rents in San Francisco Bay Area." *Transportation Research Record: Journal of the Transportation Research Board* 1606 (1): 40–50.

Krebs. Charles J. 1985. *Ecology: The Experimental Analysis of Distribution and Abundance*. New York: Harper and Row.

———. 1989. *Ecological Methodology*. New York: Harper and Row.

Kuethe, Todd H. 2011. "Measuring Local Aggregate House Prices." *International Real Estate Review* 14 (1): 118–29.

Lancaster, Kelvin J. 1966. "A New Approach to Consumer Theory." *Journal of Political Economy* 74 (2): 132–57.

McMillen, Daniel P. 2001. "Polycentric Urban Structure: The Case of Milwaukee." *Economic Perspectives, Federal Reserve Board of Chicago* 25 (2): 208–17.

———. 2003. "Spatial Autocorrelation or Model Misspecification?" *International Regional Science Review* 26 (2): 208–17.

———. 2006. "Testing for Monocentricity." In *A Companion to Urban Economics,* ed. Richard J. Arnott and Daniel P. McMillen. Malden, MA: Blackwell Publishing.

Mueller, Julie M., and John B. Loomis. 2008. "Spatial Dependence in Hedonic Property Models: Do Different Corrections for Spatial Dependence Result in Economically Significant Differences in Estimated Implicit Prices?" *Journal of Agricultural and Resource Economics* 33 (2): 212–31.

Munroe, Darla K. 2007. "Exploring the Determinants of Spatial Pattern in Residential Land Markets: Amenities and Disamenities in Charlotte, NC, USA." *Environment and Planning B: Planning and Design* 34 (2): 336–54.

Parker, Dawn C., and Vicky Meretsky. 2004. "Measuring Pattern Outcomes in an Agent-Based Model of Edge-Effect Externalities Using Spatial Metrics." *Agriculture, Ecosystems, and Environment* 101 (2–3): 233–50.

Patton, Myles, and Seamus A. McErlean. 2003. "Spatial Effects within the Agricultural Land Market in Northern Ireland." *Journal of Agricultural Economics* 54 (1): 35–54.

Razin, Eran, and Mark Rosentraub. 2000. "Are Fragmentation and Sprawl Interlinked? North American Evidence." *Urban Affairs Review* 35 (6): 821–36.

Rempel, R. 2008. *PatchAnalyst for ArcGIS.* Thunder Bay, ON: Center for Northern Forest Ecosystem Research (Ontario Ministry of Natural Resources), Lakeland University Campus.

Rogers, William H. 2006. "A Market for Institutions: Assessing the Impact of Restrictive Covenants on Housing." *Land Economics* 82 (4): 500–12.

Rosen, Sherwin. 1974. "Hedonic Prices and Implicit Markets: Product Differentiations in Pure Competition." *Journal of Political Economy* 82 (1): 34–55.

Song, Yan, and Gerrit-Jan Knaap. 2004. "Measuring the Effects of Mixed Land Uses on Housing Values." *Regional Science and Urban Economics* 34 (6): 663–80.

Ulfarsson, Gudmundur, and John I. Carruthers. 2006. "The Cycle of Fragmentation and Sprawl: A Conceptual Framework and Empirical Model." *Environment and Planning B: Planning and Design* 33 (5): 767–88.

U.S. Census Bureau. 2000. *2000 United States Census.* Available at www.census.gov/main/www/cen2000.html (accessed March 23, 2010).