Are Homeowners Willing to Pay More for Access to Parks? Evidence from a Spatial Hedonic Study of the Cincinnati, Ohio, USA Park System

Rainer vom Hofe
University of Cincinnati

Oana Mihaescu
HFI, Handelns Forskningsinstitut

Mary Lynne Boorn
University of Cincinnati

Received: 08/04/2017
Accepted: 11/28/2017

Abstract

This paper examines the impacts of the City of Cincinnati urban park system on residential property values using two local spatial hedonic model specifications: the spatial Durbin error model (SDEM) model, and the spatial lag of X model (SLX). Specifically, we examine how the distance to parks, the size of the nearest park, and the presence of park facilities for recreational activities, affect property values. Our results show that decreasing the distance to a park by one meter appreciates of the value of the average house in our sample by \$3.44 to \$6.27. A one hectare increase in the park size appreciates house values by \$22.24 to \$22.48 and the presence of park facilities for recreational activities depreciates house values by an estimated \$4,612 to 5,300 for properties within a 500 meter radius to the nearest park.

1 Introduction

Cincinnati has enjoyed a long-standing tradition of public parks. The formation of the Cincinnati Board of Park Commissioners in 1906 and the master plan for Cincinnati's parks A Park System for the City of Cincinnati by George Kessler in 1907 laid the foundation for what has become one of the nation's most recognized urban park systems. Cincinnati Parks is ranked 7 on the ParkScore® in 2015, published by The Trust for Public Land. One hundred years later, Cincinnati City Council adopted the Cincinnati Parks 2007 Centennial Master Plan, which guides the Cincinnati Board of Park Commissioners' mission "to conserve, manage, sustain, and enhance parks' natural and cultural resources and public greenspace for the enjoyment, enlightenment and enrichment of the Cincinnati community" for the decades to come. Today, the City of Cincinnati park system entails over 5,000 acres of city parklands, including five regional parks, 70 neighborhood parks, and 34 nature preserves, numerous natural areas and scenic overlooks, and a total of 50 miles of hiking and bridle trails. The park system amounts to approximately ten percent of Cincinnati's total land area, including the Cincinnati Zoo.

While voters supported the Cincinnati Board of Park Commissioners' mission, they declined the slight property tax increase necessary to maintain and improve the parks system. In the 2015 election, Cincinnati voters overwhelmingly rejected a bill to add a one mill tax levy that would have raised an estimated \$5 million annually to improve the existing park system and expand bike trails in the area. Many local governments face increasing financial pressure to balance budgets amidst rising expenses without increasing revenues.

Municipalities undergoing such constraints are often forced to make difficult spending decisions, putting at risk parks and recreation funding. Meanwhile, cities experiencing high growth have a different problem of maintaining parks and green spaces where market demands challenge withholding valuable property from private development. A better understanding of how residential property values benefit from proximity to city parks could have been useful to policy makers as well as voters.

There exists a strong foundation of research to determine the effect of public urban green space and park proximity on residential property values (Nicholls, 2004; Crompton, 2004, 2005; Kovacs, 2012; Czembrowski and Kronenberg, 2016).[1] Generally, the literature indicates increases in property values attributable to park and/or green space proximity with the degree of impact depending on the park type, park size and specific neighborhood/property characteristics, as well as some neutral or negative effect on values of properties directly surrounding smaller, recreation intensive parks. More recent studies consider the possibility for spatial dependence among residential properties. Spatial dependence refers to the fact that real property values are determined not only by their structural or neighborhood characteristics, but also by sales prices of the neighboring properties; a phenomenon that can be explained when considering that realtors, sellers, and buyers price a property based on the value of nearby properties. Ignoring the presence of spatial dependence yields inconsistent and/or biased parameter estimates. Research methods that combine spatial hedonic pricing models with geographical information systems (GIS) based analysis reveal the nuances of property value based on proximity and provide a better understanding of property value creation through park investments. This information will be useful to policy makers and public managers as it allows for a more balanced view of park investments through quantifying the commensurate benefits of parks beyond the more obvious cost-based structure that currently exists.

This study evaluates the role of parks in determining residential property values in Cincinnati, Ohio. While applying spatial econometric techniques, we account for multiple ways in which parks can affect residential property values. Foremost, we believe that distance to the closest park matters. The closer a property is located to a city park, the larger the expected positive impact on its value (Crompton, 2001, 2005; Espey and Owusu-Edusei, 2001; Kovacs, 2012; Jim and Chen, 2010; Lin et al., 2013). Next, we see the size of a park to be an important factor. Larger parks offer more amenity value and thus should also have a larger impact on property prices when compared to smaller parks (Bolitzer and Netusil, 2000; Espey and Owusu-Edusei, 2001; Kong et al., 2007; Lin et al., 2013). Last, we differentiate between active and passive parks. Active parks are all parks that offer facilities for recreational activities, including, but not limited to basketball courts, soccer fields, baseball fields, tennis courts, play grounds, golf courses, boat docks, and swimming pools. Passive parks are generally accessible and walkable, but without any specific installations to facilitate group, sport, or other activities. There is no clear consensus on whether or not nearby residents prefer active or passive parks, as this may depend widely on the socio-economic characteristics of the residents (e.g., number of children). However, the presence of facilities should have an influence on how residents perceive the parks (Espey and Owusu-Edusei, 2001; Lutzenhiser and Netusil, 2001; Shultz and King, 2001; Kovacs, 2012; Lin et al., 2013).

Our study contributes significantly to the urban economics and urban planning literature on urban parks. It explicitly accounts for the phenomena of local spatial dependence by means of a spatial Durbin error model (SDEM) and a spatial lag of X (SLX) model to better control for spatial autocorrelation and to better isolate the effect of parks on nearby property values. From a methodological point of view, accounting for local spatial dependence among properties will result in consistent and unbiased parameter estimates, a fact often neglected in traditional regression techniques that ignore the phenomenon of spatial dependence between residential properties. Using a local spatial hedonic pricing framework also allows us to separate the direct effects on the subject property from any local spillover effects attributable to neighboring properties. Finally, we contribute to the existing literature by comparing the effects Cincinnati's parks have on residential values using different buffer zones. The outline of the paper is as follows. In Section 2, we briefly discuss the theory of hedonic prices and the relevant, but still sparse literature on city parks and their impacts on house prices within the hedonic framework. Section 3 presents the data set, the study area and the empirical econometric models using georeferenced data and in section 4, we discuss our empirical results from two spatial model specifications. In Section 5, we present conclusions.

[1] Among others.

2 Review of Relevant Literature on Urban Parks and Open Spaces

2.1 The Theory of Hedonic Prices

Our research design is derived from Lancaster's consumer theory (1966) and rooted in Rosen's (1974) model of hedonic prices. Hedonic price modeling is based on product variety, where commodities are differentiated into subtypes and each subtype is treated as a good in its own right (with its own quantities and its own prices on the market). Each subtype, then, can be defined in terms of its characteristics. According to Rosen (1974), hedonic prices are the implicit prices of these characteristics and are revealed to economic agents from observed prices of differentiated products and the specific amounts of characteristics associated with them. It is these intrinsic characteristics, and not the good per se, that are bearing utility for which consumers are willing to pay (Lancaster, 1966).

As Freeman et al. (2003) explains, for the particular case of housing, to apply the hedonic pricing theory one needs to assume that the housing market is in equilibrium. Then, the rental price of a jth residential property (R_j) can be considered a function of its structural (e.g., size, number of rooms, age, etc.), neighborhood (e.g., quality of local schools, accessibility to parks, crime rates, etc.), as well as location-specific characteristics (e.g., local air, water quality, etc.), Q_j:

$$R_j = R(Q_j) \tag{1}$$

Assuming an individual occupies property j, her utility is given by:

$$u = u(z, Q_j) \tag{2}$$

where z is a composite good with a price of 1. The individual maximizes u subject to a budget constraint:

$$M - R(Q) - z = 0 \tag{3}$$

The typical first-order condition for the choice of characteristic q (included in the bundle Q) is:

$$\frac{\delta R(Q)}{\delta q} = \frac{\delta u/\delta q}{\delta u/\delta z} \tag{4}$$

If the hedonic price function $R(Q)$ is estimated for an area, its partial derivative with respect to q gives the implicit marginal price of q; this is, in other words, the additional amount that must be paid to move to a property with a higher level of that particular characteristic, all other things being equal. An individual maximizes utility by simultaneously moving along each marginal price until she reaches a point where her marginal willingness to pay for an additional unit of q equals the marginal implicit price of q. At this point she is in equilibrium.

To identify the marginal willingness-to-pay function for q, a second stage of the hedonic technique combines quantity and implicit price information (Freeman et al., 2003). The marginal willingness-to-pay function can be thus estimated through:

$$b^{*j} = b^{*j}(q, Q^*_{-q}, u^*) \tag{5}$$

where b^{*j} is the chosen utility maximizing bundle of characteristics for individual j, Q^*_{-q} includes all the characteristics of the property except q, held fixed at some level, and u^* is a constant utility achieved by maximizing equation (2) subject to (3). This means that, if the quantities of other characteristics do not change, the welfare change of an individual associated with changes in q can be estimated by (5).

Using this model, we will econometrically estimate marginal implicit prices by regressing the price of a product on its characteristics. Consequently, the price of a property will be regarded as a function of all of its characteristics–including structural characteristics (i.e., size of the building and number of bathrooms), the distance to the nearest park, the size of the nearest park, and the presence of a facility inside the park–plus a random error term. Since accessibility to and attributes of parks and open spaces are considered neighborhood characteristics (Freeman et al., 2003), we can in this way determine the willingness to pay for them through the hedonic price model.

2.2 Empirical Work on Urban Parks

Urban parks have long been valued for providing cities with oases from the surrounding density of commercial and residential uses. Credited with many environmental, social, and health benefits, these open spaces offer one of the few options for residents to enjoy recreational venues in a natural setting at little or no cost. In the face of budgetary constraints and limited resources, public officials and policy makers are pressed to quantify park benefits to justify spending public financial resources on urban parks. As early as 1850, Frederick Law Olmstead presented the theory that property value increases surrounding New York City's Central Park would more than pay for any park improvements (Crompton, 2005). This argument served as the basis for park developments throughout the United States through the 1930's (Crompton, 2004). However, early research techniques often overstated the increase in residential property value by failing to properly extract any parks-related property value premiums from a long list of property specific attributes, such as size or number of bedrooms.

The development of the hedonic pricing model (Lancaster, 1966; Rosen, 1974) finally allowed researchers to better isolate value changes attributed to a variety of housing and neighborhood characteristics, including park-related attributes. While the majority of these studies found that the presence of parks and open spaces enhances the values of the surrounding properties, the magnitude of these increases vary widely depending on the park type and size, and property distance from the closest park (Crompton, 2004; Nicholls, 2004; Czembrowski and Kronenberg, 2016; Lin et al., 2013).

The distance of a residential property to its closest park has a significant effect on its property value. In an early hedonic price study, Correll et al. (1978) found that the closer properties were to greenbelts, the higher the positive impact and that this positive impact is measurable of up to 3,200 feet. In a 2001 literature review based on 30 studies, Crompton concluded that the majority of value increases due to park proximity takes place within the first 500 - 600 feet from the closest park, though most studies used 2,000 feet as an appropriate distance cutoff value (Crompton, 2001). Further supporting these conclusions, Lutzenhiser and Netusil (2001) looked at distance bands around parks and found that urban parks' greatest influence was within the first 600 feet. For larger natural parks, this distance of greatest influence extended to 800 feet, while a strong positive influence still was measurable as far as 1,500 feet away. Likewise, more recent studies confirm that property values are positively affected by park proximity and expand the literature to include additional park and location considerations in determining the effects of park proximity on value (Kong et al., 2007; Jim and Chen, 2010; Kovacs, 2012; Lin et al., 2013; Czembrowski and Kronenberg, 2016). Based on these studies, property values generally increase with proximity to parks and green space, yet the impact of distance from a park on property values often varies with specific park and neighborhood characteristics.

According to the literature, the way parks are being used–park type–has a significant impact on how these parks influence residential property values. Generally, parks providing more natural landscapes and passive uses tend to have a greater, positive impact on surrounding residential values than smaller, more intensely used parks (Crompton, 2004). Both Lutzenhiser and Netusil (2001) and Shultz and King (2001) separated parks into categories depending on their use, and found that natural parks, particularly the largest one in the study, had the greatest positive impact on surrounding property values, over smaller specialty parks with more intense recreational uses. Echoing these results, Lin et al. (2013) found that passive parks, especially those with a water feature, had the greatest positive impact on property values, whereas heavily used active parks had little or even negative impacts on value. Generally, larger parks have a greater positive impact on proximate residential properties (Czembrowski and Kronenberg, 2016; Kong et al., 2007). Another important factor in determining value impacts is the quality of the park. Espey and Owusu-Edusei (2001) categorized parks using size and attractiveness as the primary criteria and found that smaller, poorly maintained parks with playgrounds had a negative impact on the properties closest to the park. The greatest positive influence on property values occurred in areas surrounding larger, well-kept parks (Espey and Owusu-Edusei, 2001). Irwin (2002) argues that it is primarily the existence of permanent green space that impacts properties and to a lesser extent the amenities of the parks. Additionally, lack of available green space has a greater positive impact on properties located near permanent open spaces (Crompton, 2005; Conway et al., 2010;

Czembrowski and Kronenberg, 2016; Kong et al., 2007). Furthermore, residential property type also impacts the benefit of park proximity with high-rise residential properties (Jim and Chen, 2010) and apartments and terrace style housing having greater value increases from park proximity than less dense residential property types (McCord et al., 2014).

The general findings that larger, more natural parks and open spaces have a greater positive impact on value than small, more intensely used parks is of particular interest (Lutzenhiser and Netusil, 2001; Shultz and King, 2001; Crompton, 2004; Anderson and West, 2006; Kong et al., 2007). With our study, we will add to the presented literature by looking specifically at parks in an urban setting and disseminating how park size, park amenities, and property distance to parks influence surrounding property values.

3 Methods

3.1 Data and Descriptive Statistics

In order to investigate the effects of parks on residential property values, we combined two databases: i) the Cincinnati Area Geographical Information System (CAGIS), and ii) the Hamilton County Auditor's sales data. The CAGIS database contains information on all parks located in the City of Cincinnati, as well as structural housing characteristics for single-family residential properties. From the CAGIS database, we excluded all smaller green spaces, which for unknown reasons were included in the parks database–such as green spaces next to roads and highways, landscaping around street intersections, schools, and churches, etc.–and as such do not serve any recreational purpose. A summary of the 182 parks included in the analysis is provided in Table 1; a map showing the parks in Figure 1.

Table 1: Parks Summary Statistics (N=182)

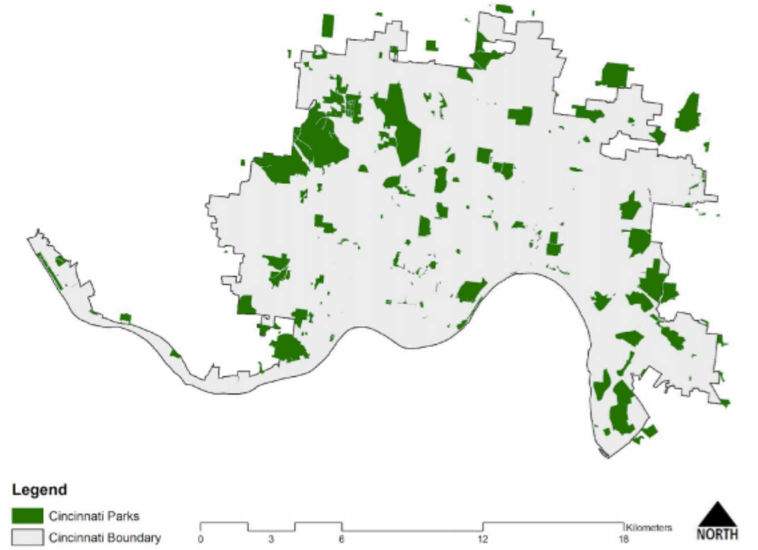
Variable Statistic	Park Size (Hectares)	Park Facility (1=Yes, 0=No)
Mean	19.6	0.340
Standard Deviation	52.8	0.474
Max	576.1	1
Min	0.018	0

The average park in our study is 19.6 hectares in size. The largest park, Mt. Airy Forest, is 576.1 hectares in size, while the smallest parks, Delhi Pike Preserve, is merely 0.018 hectare. The standard deviation of 52.8 hectares reflects upon a wide variation in park size. More than half the parks (102) are smaller than 5.0 hectares and only 24 parks are larger than 40.0 hectares. Altogether, the Cincinnati Park Board manages a total of 109 parks included in our study. The remaining 73 parks included in our study are registered under the ownership of conservation groups; or are state, county, or township parks. Of the 182 parks, 158 lie entirely within the city. We also included 24 parks that lie either partly or completely outside the city boundary to ensure that houses on the edge of the city can have their closest park outside the city.

We identified 36,167 single-family residential properties in the City of Cincinnati that lie within close proximity to one of the 182 parks, for which we were able to retrieve information, including total market values, from the Hamilton County Auditor's Office (`http://hamiltoncountyauditor.org/transfer_policies.asp`). Following Crompton (2001) and Lin et al. (2013), we included residential properties lying within a 500 meter buffer zone around the parks. Although the literature provides no clear consensus on the size of the buffer zone, we regard 500 meter as acceptable walking distance to a park. Also, many of our included parks are larger in size and do offer amenities, which supports our decision for choosing the 500 meter maximum Euclidean distance measure.

We use total market values of single-family residential properties as the dependent variable (Leigh and Coffin, 2005; Cotteleer and van Kooten, 2012; Mihaescu and vom Hofe, 2013; Parent and vom Hofe, 2013). The Hamilton County Auditor defines "Market Total Value" as the most probable sale prices of the properties

Figure 1: Parks Included in the Analysis



in an open and competitive market with a willing buyer and seller (Hamilton County Auditor)[2]. By contrast, the term "assessed value" under Ohio law is the taxable value which is 35 percent of the market value. To avoid confusion between the meaning of "assessed value" used in Ohio to mean taxable value and that employed in the academic literature to mean appraised value, we use the term "market values" for all property values that have been appraised by the county auditor's office. Cotteleer and van Kooten (2012) provide a comprehensive comparison of the pros and cons of using either sales prices or market values, adding to the ongoing debate on whether to use sales data or appraised market values. Generally, market values are easier to come by and result in larger sample sizes, an important fact, when using spatial econometric models. We have, for instance, 36,167 observations when using market values, versus 6,184 observations when using sales prices for a three-year period (2008-2010). Ventolo and Williams (1994) argue that the appraised market value should come close to actual sales prices for all arm's length transactions. In the City of Cincinnati for this matter, sales prices are entered by the county auditor as market values in the tax record, when properties change hand. Berry and Bednarz (1975) and Nicholls and Crompton (2005) also support the idea that market value is good proxy of what a property would sell for. Using market values further has an advantage in distressed neighborhoods or during periods of economic crisis (Leigh and Coffin, 2005). Using sales data has further the disadvantage when sales do not occur frequently, e.g., during periods of economic crisis or in depressed neighborhoods (Leigh and Coffin, 2005; Cotteleer and van Kooten, 2012). Trading between relatives may also distort sales prices . One the disadvantage of appraised market values is that they are prone to errors when appraising residential properties (Freeman et al., 2003). Thus, the relationship between market values and property characteristics (and, consequently, associated regression coefficients) may be biased (du Preez and Sale, 2014). du Preez and Sale (2014) also uncovered clear differences between the distributions of sales prices and market values, with actual prices being, on average, lower than market values. Ihlanfeldt and Taylor (2002) argue that researchers need to be aware of the fact that appraised market values may lag behind the changes in actual property values, particularly in fast-appreciating neighborhoods. In addition, real estate agents may influence the market by affecting the list price of properties and the bidding strategies of buyers. Lenders may affect the market through their practices, e.g., by requesting large deposits for first-time buyers (Doss and Taff, 1996). The discussion between which of these two proxies, appraised market values or actual sales prices, is closest to what a property would sell for in todays market is still open (Cotteleer and van Kooten, 2012). Importantly, the estimation results reveal similar economic interpretation.

The explanatory variables included in our model fall into two main categories: structural characteristics of the property and neighborhood characteristics, including the park-related attributes. Guided by the

[2]`http://hamiltoncountyauditor.org/hamilton_glossary.asp`

relevant hedonic literature, we included the following explanatory structural characteristics: the lot size (*sizeland*), the size of the house in square meters (*sizehouse*), the number of bathrooms (*bathrooms*), the age of the house (*age*), and the car capacity of the basement garage (*garage*) (Hess and Almeida, 2007; Cebula, 2009; Landry and Hindsley, 2011). Following Bin et al. (2008), we added a variable denoting the condition of the house, which includes seven categories, as defined by the Hamilton County Auditor's Office: very poor, poor, fair, average, good, very good, and excellent. We argue that the property condition is an important contributor in determining its market value. We define the middle condition category (average) as the baseline in our regression model. Consequently, we expect that houses in worse than average condition (very poor, poor, or fair) will have lower values, while houses in better than average condition (good, very good, or excellent) will have higher values. Definitions and summary statistics for the variables used in our analysis are presented in Table 2.

Table 2: Variables: Definitions and Summary Statistics (n=36,167)

Definition (Abbreviations in parenthesis)	Mean	Median	Minimum	Maximum
Market values of single-family residential properties (P)	122,852	96,300	10,000	668,750
Structural characteristics of the property:				
Size of the land, in hectares (*sizeland*)	0.074	0.056	0.005	2.017
Size of the building, in square meters (*sizehouse*)	162.943	146.601	22.297	547.756
Total number of bathrooms (*bathrooms*)	1.709	1.500	0.000	8.000
Age of the building, in years (*age*)	83.878	85.000	1.000	210.000
Basement garage capacity, # of cars (*garage*)	0.335	0.000	0.000	8.000
Condition of the house:				
very poor ($cond_{vpoor}$)	0.005	0.000	0.000	1.000
poor ($cond_{poor}$)	0.016	0.000	0.000	1.000
fair ($cond_{fair}$)	0.096	0.000	0.000	1.000
average ($cond_{average}$)	0.455	0.000	0.000	1.000
good ($cond_{good}$)	0.362	0.000	0.000	1.000
very good ($cond_{vgood}$)	0.065	0.000	0.000	1.000
excellent ($cond_{excellent}$)	0.001	0.000	0.000	1.000
Neighborhood characteristics:				
Poverty rate (*poverty*)	26.469	24.000	2.500	82.500
% of people with bachelor degree (*bachelor*)	30.859	26.900	1.300	82.500
Crime rate (*crime*)	18.886	17.916	0.000	62.857
Public school performance indicator (*school*)	84.521	83.200	68.800	111.800
Distance to the closest park, in meter (*parkdist*)	248.930	245.438	0.000	499.997
Size of the closest park, in hectares (*parksize*)	45.081	11.569	0.018	576.135
Presence of park facility (*parkfacility*)	0.375	0.000	0.000	1.000

The poverty rate (*poverty*), crime rate (*crime*), and educational attainment (*bachelor*) are three commonly used neighborhood characteristics (Lynch and Rasmussen, 2001; Geoghegan, 2002). We use the 129 Census tracts in the City of Cincinnati as neighborhood proxy in our study. Poverty rates and educational attainment were obtained from the 2010 US Census. The poverty rate is defined as the percentage of the population below the poverty line; educational attainment refers to the percent of people with a bachelor's degree. We define the crime rate as number of crimes / (*population*/1000). Crime data are publicly available for 2012/2013 from the City of Cincinnati police department. Only property-related crimes (i.e., aggravated burglary; inflicted harm; aggravated arson; breaking and entering; burglary; criminal trespassing; fire weapon into habitat; property damage; safecracking; tampering with coin machine; unauthorized use of property; and non-school vandalism) are considered for this analysis, since non-property related crimes can take place randomly through the whole city and are thus not specifically related to real-estate properties. In addition, we include school district information to control for neighborhood characteristics (Brasington and Haurin, 2006; Clapp et al., 2008; Dougherty et al., 2009). Specifically, we use a performance indicator for public schools, made available by the Ohio Department of Education (http://reportcard.education.ohio.gov/Pages/default.aspx).

The variables of interest in our study are the Euclidean distances from each property to the closest park (*parkdist*) in meter, the size of the closest park (*parksize*) in hectares, and the presence [absence] of park facilities in the closest park (*parkfacility*). With the park facility binary variable, we distinguish between natural green space and parks with built facilities, such as tennis, basketball, or soccer courts. Regarding the distance measure (*parkdist*), we chose Euclidean over network distances for numerous reasons. First, Euclidean distances are conceptually straight forward, are easy to compute, and have been successfully used to capture location-related neighborhood characteristics in previous studies (Troy and Grove, 2008; Conway et al., 2010). Earlier studies by Newell (1980) and O'Sullivan and Morrall (1996) reported that network distances are approximately 1.20 to 1.23 times the Euclidean distance in an urban environment, while Sander et al. (2010a) found the mean of the differences in distance to be as high as 48.4%. Further, while Sander et al. (2010b) argue that road distances better reflect of actual travel distances to the nearest park, we follow Eiser et al. (2007) who argue that Euclidean distances should be preferred to network (street) distances when the perception of being in close proximity to the investigated feature is more important for housing prices than accessibility. With respect to parks, either argument has some validity as some residents perceive parks as a pleasant amenity. Without setting a foot into a park, they understand that parks build communities and create a sense of place, thus contributing to a higher quality of life. Other residents see parks as a welcome opportunity to walk their dogs, get some exercise through running, playing tennis or basketball, or just socialize. While we do not know the specific percentages of active park users, we assume that residents perceive nearby parks as a positive amenity. Last, the majority of parks can be accessed literally from anywhere on foot. Consequently, it would be almost impossible to identify all park entrance points.

According to the statistics reported in Table 2, the average house in our study has a market value of \$122,852. Our average house has 162.9 square meter, 1.71 baths, and is built on a 742 square meter lot. The majority of houses in our study area are in either average (45.52%) or good condition (36.17%). Just under 12% are in below average condition, while 6.65% are in above good condition. With respect to the neighborhood characteristics, the average house is located in a Census tract with 26.5% of households living below the poverty line, with 18.9 property-related crimes per 1,000 inhabitants, where 30.9% of the population has at least a bachelor's degree, and with an average school performance indicator of 84.5. Important for our study is that the average house is located 248.9 meter away from the nearest park. This specific nearest park is 45.1 hectares in size and there is a 37.5% chance that this nearest park includes some type of facility.

3.2 Empirical models

The centerpiece of this research is a hedonic price model, where potential buyers value the elements of the bundle that compose a housing unit. The bundle is made up of structural and neighborhood characteristics, including park characteristics. Following LeSage and Ha (2012) and Mihaescu and vom Hofe (2013), we applied a Bayesian spatial Durbin error model (SDEM), defined as:

$$\begin{aligned} lnP = \alpha + S * \beta + N * \gamma + W * S * \theta + C * \varphi + u \\ u = \lambda * W * u + \epsilon \\ \epsilon \sim N(0, \sigma_\epsilon^2 I_n) \end{aligned} \tag{6}$$

where lnP is a vector of log-transformed market values of single-family residential properties in the City of Cincinnati; S is a matrix of structural characteristics of the properties, C is a matrix of quadratic controls of longitude and latitude, and N is a matrix of neighborhood characteristics, including the distances from each property to the closest park (*parkdist*), the sizes of the closest park (*parksize*), and the presence of park facilities (*parkfacility*). The four vectors β, γ, θ, and φ are the corresponding parameters to be estimated and W is the spatial weight matrix. The fact that economic theory does not imply the functional form of hedonic models (Bolitzer and Netusil, 2000) and the common practice of using log-transformed prices, while not transforming distance measures (Czembrowski and Kronenberg, 2016), we chose a log-linear functional form due to its dominance in the relevant literature, to better control for the large variations in assessed values (Svetlik, 2007), and to account for the possibility of non-linear relationships (Troy and Grove, 2008; Bolitzer and Netusil, 2000). We include quadratic controls of longitude and latitude to control for location effects. Following Ross et al. (2011), there is a chance of biased coefficients and inflated standard errors when using only one distance variable (e.g., distance to nearest park). This specification problem arises as distance variables serve as proxies for the relative position of every property in space. Without properly identifying residential houses in space, the specific benefit of parks valued by households may be biased. The problem can be solved by adding a second distance variable (Deaton and Hoehn, 2004) or by using quadratic controls of longitude and latitude (Ross et al., 2011).

The wide-spread practice of realtors, sellers, as well as buyers to price a real estate property based on market values and structural characteristics of neighboring residential properties explains the presence of spatial spillovers. Maslianskaïa-Pautrel (2016) discuss the spatial diffusion process coming from neighbors – the local spillovers – and distinguish it from the spatial multiplier effect, a result of the feedback effects that literally spread across the entire study are – the global spillovers. As a result, the price of a property is influenced not only by its own characteristics, but also by the characteristics of the neighboring properties (Cohen and Coughlin, 2008; Conway et al., 2010; Izón et al., 2010), which then violates the assumption of traditional OLS models of the independence of observations, or:

$$E(\epsilon_i \epsilon_j) = E(\epsilon_i)E(\epsilon_j) = 0 \tag{7}$$

This assumption does not hold in the presence of spatial externalities; consequently, the use of OLS produces biased and/or inconsistent coefficient estimates (Anselin, 1988; LeSage and Pace, 2008; Brown et al., 2009). To address this issue, OLS should be replaced by a spatial regression model.

Inspired by LeSage (2014), we initially applied the spatial Durbin model (SDM) and the spatial Durbin error model (SDEM) to our data set. The conceptual difference between these two model specifications is that the SDEM treats spatial spillovers as a pure local phenomenon, while the SDM assumes spatial dependence to be a global phenomenon. The initial results clearly favor the SDEM, which confirms LeSage and Pace's (2014) argument that "most spatial spillovers are local". The SDEM allows for spatial spillover effects only between neighboring residential properties as defined in the spatial weight matrix (W) and are presented in the SDEM by a matrix of spatial lags for the explanatory variables ($W * S$). W is a contiguity row-normalized weights matrix that defines properties as neighbors if they are contiguous at any point. The definition of the lagged explanatory variables allows, according to LeSage (2014), for the own-property partial derivatives to equal the estimated coefficients, for example $\frac{\delta(lnP)_i}{\delta S_i^k} = \beta^k$ for the case of S^k, the structural house characteristics k. Cross-partial derivatives $\frac{\delta(lnP)_i}{\delta S_j^k} = W * \theta^k$ illustrate the local nature of spatial spillovers for structural house characteristics, k, from neighboring properties. It is further noticeable that the spatial lag component is restricted to only the structural characteristics of the property (S) in order to avoid multicollinearity problems between the other explanatory variables (i.e., N) and their corresponding lags. Almost any two neighboring properties (i, j) in our sample will share the same nearest park, of the same size and hosting the same facilities. This also results in the distance from property i to the closest park being very similar to the distance from its neighbors to the closest park. In addition, neighboring properties share the same neighborhood and school district characteristics. The presence of severe multicollinearity makes the coefficient estimates inefficient and/or unstable (Mihaescu and vom Hofe, 2013).

As explained above, we chose a model (SDEM) that includes only local spillovers, in other words, does not include the so-called feedback effects. However, the SDEM model uses a spatial autoregressive specification for the disturbances (u), which allows for global diffusion of shocks in the disturbance structure ($u = \lambda * W * u + \epsilon$), increasing the efficiency of the coefficient estimates. As $\lambda > 1$, impacts decay with the order of neighbors (LeSage and Pace, 2014). The errors from the disturbances (ϵ) are normally distributed, with a zero mean and a variance σ_ϵ^2. In addition to the SDEM specification, we also include a second local model specification, the spatial lag of X model (SLX), a special case of the SDEM specification, when $\lambda = 0$. The SLX model is expressed as follows:

$$lnP = \alpha + S * \beta + N * \gamma + W * S * \theta + C * \varphi + \epsilon \qquad (8)$$
$$\epsilon \sim N(0, \sigma^2 I_n)$$

which resembles the SDEM model, but without the spatially autocorrelated error term (u). A second special case of the SDEM and widely used spatial regression model to capture local spillovers, the Spatial Error Model (SEM), has not further been considered as the estimated parameters $\hat{\theta}$ for the lagged explanatory variables in the SDEM results are statistically significant and as such justify the use of the SDEM specification. Due to the fact that spatial dependence of residential property prices is purely local in nature, we argue on theoretical ground to exclude any global spatial model specification, such as the spatial Durbin model (SDM) or the spatial autoregressive (SAR) model, from our empirical analysis (see also LeSage and Pace (2014), for a detailed discussion on the correct model specification for empirical analysis).

4 Discussion of empirical results

Our regression results regarding the effects of parks on the market values of single-family residential properties in the City of Cincinnati are presented in Table 3. We show the results of the SDEM model, as well as the SLX estimation results for comparison purposes. We observe that the SDEM model shows a slightly better fit compared to the SLX specifications with an Akaike Information Criterion of 61,516 for the SDEM model and 63,697 for the SLX model. The spatial coefficient (λ) of 0.3876 in the SDEM model is significant at the 99% confidence level supporting our choice of a spatial regression model. We use a Bayesian estimation process for all two hedonic price models and correct for heteroscedastic disturbances following (LeSage, 1999). The variance inflation factors ranging from 1.003 to 2.431 indicate that no multicollinearity is present.

Included in the SDEM and SLX models are direct and spillover effects. Since the main diagonal of the matrix W contains zeros and the rows of the matrix W sum to one, all estimated coefficients except for θ in equations (1) and (3) represent direct effects, while the θ coefficients represent the spillover effects (LeSage, 2014). The log-linear model specifications in combination with the local spatial spillovers allow a direct interpretation of the estimated parameters in Table 3 for both model specifications as a percent change in property value for a one unit change in the explanatory variable. For both model specifications, the regression estimates β and θ should be unbiased. Adding the spatial dependence to the disturbances in SDEM model estimation adds efficiency to the process when compared to the SLX model. Also, including the quadratic controls of longitude and latitude avoids potential bias issues when using only one distance measure. However, because these estimated φ parameters have no practical meaning, we abstained from including them in our final results table.

The coefficient estimates for the direct effects in the SDEM corresponding to the structural characteristics of the property all have the expected signs and are significant at the 99% confidence level. The average residential property in our sample is valued at $122,852 and lies 248.9 meters away from the nearest park. Increasing the size of the land by 1 square meter implies an average increase by 0.0053% in the market value of a property, which is equivalent to $6.51 per square meter, for our average house value of $122,852. Adding 1 square meter to the building increases its market value by 0.27%, or $330. Accordingly, one more bath adds 5.15% ($6,328) and increasing the capacity of the basement garage by one car adds 2.75% ($3,375) to the market value of our average property. The age coefficient has the expected negative sign, signaling that the market value of a property depreciates with age (in this case, by 1.06% ($1,303) for every year of age). A positive $age_{squared}$ coefficient shows then that the age-specific depreciation effect slows down over time at a rate of 0.0038% per year. As expected, the condition of the house is a major contributor to its value, but the interpretation of the estimated categorical parameters needs some further explanation. The estimated constant in our SDEM model of 10.074268 translates into $e^{10.201645} = \$26,943$ for a house that is in average condition. This base price changes, however, as the condition of the house either worsens or improves. For example, the base value of a house in good condition increases by 0.135936 to $e^{10.337401} = \$30,866$ meaning that a house in good condition is worth $3,923 more than a house in average condition, everything else being equal. Accordingly, a house in very good condition is worth $9,104 more and a house in excellent condition

Table 3: Effects of Parks on Residential Property Values in the City of Cincinnati (n = 36,167)

Variables	SDEM		SLX	
	Parameter	p-Value	Parameter	p-Value
$constant$	10.201465	<0.01	10.211803	<0.01
Structural characteristics of the properties				
$sizeland$	0.000053	<0.01	0.000048	<0.01
$sizehouse$	0.002684	<0.01	0.002859	<0.01
$bathrooms$	0.051512	<0.01	0.055278	<0.01
age	-0.010605	<0.01	-0.010174	<0.01
$age_{squared}$	0.000038	<0.01	0.000036	<0.01
$garage$	0.027471	<0.01	0.017696	<0.01
$cond_{vpoor}$	-0.923445	<0.01	-1.072054	<0.01
$cond_{poor}$	-0.49363	<0.01	-0.514455	<0.01
$cond_{fair}$	-0.219315	<0.01	-0.211597	<0.01
$cond_{good}$	0.135936	<0.01	0.124734	<0.01
$cond_{vgood}$	0.291110	<0.01	0.262003	<0.01
$cond_{excellent}$	0.441086	<0.01	0.465527	<0.01
Neighborhood characteristics				
$poverty$	-0.001252	<0.01	-0.001140	<0.01
$bachelor$	0.011986	<0.01	0.011502	<0.01
$crime$	-0.001909	<0.01	-0.001070	<0.01
$school$	0.001646	<0.01	0.002347	<0.01
$parkdist$	-0.000051	0.018	-0.000028	<0.01
$parksize$	0.000183	<0.01	0.000181	<0.01
$parkfacility$	-0.037543	<0.01	-0.043141	<0.01
Structural characteristics of neighboring properties				
$W * sizeland$	0.000001	<0.01	0.000003	0.135
$W * sqmtrfinished$	0.000833	<0.01	0.000770	<0.01
$W * bathrooms$	0.032671	<0.01	0.026945	<0.01
$W * age$	-0.006336	<0.01	-0.005147	<0.01
$W * age_{squared}$	0.000029	<0.01	0.000024	<0.01
$W * garage$	0.038363	<0.01	0.044361	<0.01
$W * cond_{vpoor}$	-0.489707	<0.01	-0.669583	<0.01
$W * cond_{poor}$	-0.256236	<0.01	-0.282074	<0.01
$W * cond_{fair}$	-0.208881	<0.01	-0.230919	<0.01
$W * cond_{good}$	0.145953	<0.01	0.101972	<0.01
$W * cond_{vgood}$	0.307800	<0.01	0.237923	<0.01
$W * cond_{excellent}$	0.370485	0.03	0.435356	<0.01
λ	0.387626	<0.01	—	—
R^2	0.771		0.6657	
$AkaikeInformationCriterion(AIC)$	61,516		63,697	

is worth \$14,937 more than the house in average condition. Houses in worse than average condition lose \$5,306, \$10,497 or \$16,242 when their condition drops to fair, poor, or very poor respectively.

Neighborhood-related characteristics show that the poverty rate and the crime rate have, as expected, a negative impact on the sales price of a property; for every percent of the population below the poverty rate the price decreases by 0.13% (\$154) and for every extra crime per 1000-population, by 0.19% (\$235). Meanwhile, every 1% of people with bachelor's degree in the census tract increases the sales value of a property by 1.20% (\$1,473) and every 1 point increase in the school performance indicator adds 0.16% (\$202) to the market value.

Turning now to the variables of interest, the characteristics of the park located closest to each property, we find as expected that the price of a property decreases as the distance from the closest park increases. For our average property valued at \$122,852 this means that for every 100 meter increase in the distance to the closest park, the sales price of a property decreases by 0.51% (\$627), or \$6.27 per meter change in distance. As such, our finding confirms research by Correll et al. (1978), Crompton (2001); Lutzenhiser and Netusil (2001), among others, who find increases in the value of properties surrounding parks in similar magnitude using buffer zones from approximately 150 to 1,000 meter. The size of the closest park, although significant, has only a minimal influence on property prices. For our average house of \$122,852, increasing the size of its closest park by 1 hectare would merely increase its value by 0.018%, or \$22.48. Completely different is the outcome regarding recreational uses of the parks. If the closest park includes a recreational facility, the average decrease in the price of a property is of 3.75%, or \$4,612. Our results confirm earlier studies by Crompton (2004); Espey and Owusu-Edusei (2001); Lutzenhiser and Netusil (2001); Shultz and King (2001) who showed that parks providing more natural landscapes and passive uses tend to have a greater, positive impact on surrounding residential values. On the other hand, we only find a relatively small incremental value of slightly larger parks versus smaller parks, considering that our average house's closest park is 45.1 ha. It also leaves open the question for further research, whether the detrimental value of parks with recreational facilities stems from the pure presence of the recreational facility, or is attributed to its often poor condition and neglected maintenance. This issue also raises the question of what types of recreational facilities are preferred over others.

The spatial spillover effects in the SDEM model captured by the θ coefficients in equation (1) are purely of local nature (LeSage and Pace, 2014). As such, the θ coefficients capture how residential property prices are influenced by changes in structural characteristics of immediately neighboring properties. All local spillover in the SDEM model, with the exception of the $W * sizeland$ and $W * bedrooms$ coefficients, are statistically significant. Adding 1 square meter to the average house size of the adjacent properties induces an increase by 0.08% (\$102) in the market value. The other structural characteristics, averaged over neighboring properties, also induce similar, though lower, effects as compared to own structural characteristics (3.27% (\$4,014) for 1 extra bath, minus 0.63% (\$778) for 1 year of age and 0.0029% for $age_{squared}$, and 3.84% (\$4,713) for 1 more space in the averaged capacity of the basement garage). Also interesting is the relatively large impact the neighboring houses have on the average house with respect to the conditions they are in. Very poorly- or poorly maintained neighboring houses negatively affect own market values by \$10,432 and \$6,090 respectively, while properties in fair condition still depreciate own market values by as much as \$5,079. Contrarily, neighboring houses that are in above average condition positively affect own market values by \$4,234, \$9,711, and \$12,082 when they are in good, very good, and excellent condition. Due to potential multicollinearity issues, we excluded all neighborhood variables–including all three park-related characteristics and distance to the CBD–from the construction of the spatial lags in the SDEM.

When selecting the most appropriate model framework, we ended up, for reasons discussed above, with two potential spatial models: the SDEM model and the SLX model. Though the SDEM model provides the overall better fit to our data sample, the SLX model also provides some interesting findings. Comparing our direct effects from the SDEM and the SLX models confirms our general conclusions. The estimated coefficients for the SLX model all have the expected signs and are all significant, except for the lagged size of the land parameter (p = 0.135). A direct comparison of the SDEM and SLX model coefficients reveals that the majority of the estimated coefficients are similar in magnitude, but exhibit, on average, differences of 9.7% for the structural characteristics, 22.9% for the neighborhood characteristics, and 18.6% for the lagged structural characteristics. Examining the three estimated parks parameters in the SLX specification–park distance, park size, and park facility–we find that for every 100 meters increase in the distance of our property valued at \$122,852 its market value decreases by 0.28% (\$344), or \$3.44 per meter. A change in the nearest park's size by 1 hectare translates into a 0.02% (\$22.24) increase in value of our average property. The interesting finding, however, is that according to the SLX result, recreational facilities decrease the market value of the nearest residential property by 4.31% (\$5,300) which again emphasizes that residents prefer passive park uses over active ones.

One of the important choices we had to make when assessing the influences parks have on residential property values is whether or not to use a buffer zone around the parks for identifying the properties to be included in our study. Given that the relevant literature is inconclusive as to whether to apply buffer zones, or as to the size of these buffer zones, we conducted a sensitivity analysis to find out how the parks impacts differ for different buffer zones in our study area. Our findings from this sensitivity analysis are presented in Table 4.

Table 4: Sensitivity of Park Effects on Property Values with Respect to Size of Buffer Zones

Buffer Zones	Spatial Durbin Error Model *parkdist*		*parksize*		*parkfacility*		Number of Observations (n)
0-100 m	0.000022		0.000289	***	-0.029609	**	6,340
0-250 m	-0.000071		0.000249	***	-0.035509	***	18,415
250-500 m	-0.000043		0.000126	***	-0.037637	***	17,752
100-500 m	-0.000035		0.000167	***	-0.037449	***	29,827
0-500 m	-0.000051	**	0.000183	***	-0.037543	***	36,167
500-750 m	0.000015		0.000147	***	-0.038445	***	9,145
750-1000 m	0.000346	***	0.000053		-0.033261	*	3,989
500-1000 m	0.000229	***	0.000146	***	-0.037838	***	13,134
no buffer	0.000061	***	0.000141	***	-0.034785	***	51,786
Buffer Zones	**Spatial Lag of X Model** *parkdist*		*parksize*		*parkfacility*		**Number of Observations (n)**
0-100 m	-0.000131		0.000335	***	-0.044068	***	6,340
0-250 m	-0.000063	**	0.000274	***	-0.041457	***	18,415
250-500 m	-0.000015		0.000119	***	-0.044139	***	17,752
100-500 m	-0.000009		0.000152	***	-0.044089	***	29,827
0-500 m	-0.000028	***	0.000181	***	-0.043141	***	36,167
500-750 m	0.000370		0.000091	***	-0.035325	***	9,145
750-1000 m	0.000319	***	0.000063	**	-0.026550	***	3,989
500-1000 m	0.000188	***	0.000106	***	-0.035218	***	13,134
no buffer	0.000048	***	0.000122	***	-0.037216	***	51,786

* significant at the 0.10 level. ** significant at the 0.05 level. *** significant at the 0.01 level.

Not surprising, changing the distances for the buffer zones significantly affects the outcomes of the estimated parameters. First, the park distance parameter ($\gamma_{parkdist}$) switches sign with increasing distances, i.e., after 500 meters, in both the SDEM and SLX model specifications. While market values within 500 meters increase as distances to the nearest park decreases, outside the inner 500-meter buffer the results indicate that market values tend to increase with increasing distances. Unfortunately, the fact that half of the estimated park distance parameters ($\hat{\gamma}_{parkdist}$) are not significant does not allow valid conclusions to be drawn with respect to their changes in magnitude. Nevertheless, the results allow a comparison of the first 0-500 meter buffer to the second 500-1000 meter buffer. Here we find a park effect for the 0-500 meter buffer of negative \$6.27 ($\hat{\gamma}_{parkdist} = -0.000051$) per meter increase in distance from the park compared to a positive \$28.13 ($\hat{\gamma}_{parkdist} = 0.000229$) per meter in the second 500-1000 meter buffer. Both of these values are from the SDEM model in reference to our averagely priced property of \$122,852. This finding indicates not only the sensitivity of the nearest park effect on property values, but also questions the park effects on property values beyond 500 meters in our study area, or beyond what we identified as a walkable distance to the nearest park.

Second, park sizes matter regardless of how far a residential property is from the nearest park. In both the SDEM and SLX spatial model specifications (with significance of all but one estimated parameter), larger park size matters regardless of the distance to the nearest park. As expected, we find that property values generally tend to increase with an increase in park size and that the positive effect is stronger for properties closer to their nearest park. Third, park facilities do have a negative effect on property prices, as indicated by the significance of all estimated parameters in both our spatial models. For the SDEM model, the negative effect of park facilities appears to be fairly constant with respect to applied buffer zones, except the 0-100 meter zone (-0.029609), which is somewhat smaller in magnitude. For the SLX model, the effect of park facilities is definitively larger within the first 500 meters, but decreases significantly in size beyond the 500 meter threshold. To complete this sensitivity analysis of how the park facilities differ in impact across the various buffer zones in our study area, we included the estimated parameters when not using buffer zones at all. Here we find that the park facility effects are similar to the effects when applying buffer zones of greater than 500 meter. Again, the park distance parameters, while significant, do not have the expected sign.

5 Conclusion

It is a well-known fact that location matters for homebuyers and homeowners alike, and plays an important role when determining property values. In this paper, we show that urban parks have a significant influence on house prices when they are located within close proximity to a park, where the distance to the nearest park is calculated based on Euclidean distances. More specifically, using the results from a spatial hedonic pricing model that accounts for local spatial dependence among residential property prices–the Spatial Durbin Error Model (SDEM)–we evaluated three different park influences on property values. First and foremost, we find that proximity of residential properties to parks benefits property owners. The price of a property increases with decreasing distance to the closest park, which confirms previous findings. More specifically, we estimated the influence of the Cincinnati parks in Hamilton County, Ohio, to increase the average priced house of $122,852 in our sample by $6.27 when moving closer to the park by one meter. Secondly, increasing the size of a nearby park by one hectare increases the average priced house by 0.018%, or $22.48. While this confirms other research that park size maters, the magnitude of the park size influence on property values is of lesser importance in Cincinnati, which one might explain by the large number of parks within the city. Last, we find that properties located close to parks with recreational facilities can register a total decrease in the price of a property of 3.75% ($4,612) for the average property according to our results. This result raises the issue of whether the detrimental value of parks with recreational facilities stems from the pure presence of the recreational facility, or can be attributed to its often poor condition and neglected maintenance. It also leaves open the question of what types of recreational facilities are preferred over others.

In this paper, we presented a sensitivity analysis with the estimation results when using different buffer zones. Overall, we conclude that the estimated results for the three park parameters–park distance, park size, and park facility–are very sensitive with respect to the chosen buffer zone. Most interesting is the finding that with increasing distance to the nearest park, property values clearly decrease for houses within 500 meters to the park. Beyond this 500 meter buffer, we find exactly the opposite effect; with increasing distance, houses appear to appreciate in value. We also find that the bigger the park, the better. The size of the nearest park positively influences property values, regardless of the distance of the property to the nearest park. Park facilities, on the other hand, tend to negatively affect property values, if properties lie within a 500 meter distance to the nearest park. This negative influence does, however, not extend beyond the 500 meter, as indicated by our sensitivity analysis. Overall, the findings of this sensitivity analysis indicate that more research is needed to more fully understand the influence on the estimated parameters stemming from various buffer zones. In addition, individual park facilities may also have different effects on property values, a fact that suggests further research of this matter.

References

Anderson, S. T. and West, S. E. (2006). Open space, residential property values, and spatial context. *Regional Science and Urban Economics*, 36(6):773–789.

Anselin, L. (1988). *Spatial Econometrics: Methods and Models*. Kluwer Academic Publishers, Dordrecht, NL.

Berry, B. J. L. and Bednarz, R. S. (1975). A hedonic model of prices and assessments for single-family homes: Does the assessor follow the market or the market follow the assessor? *Land Economics*, 51(1):21–40.

Bin, O., Crawford, T. W., Kruse, J. B., and Landry, C. E. (2008). Viewscapes and flood hazard: Coastal housing market response to amenities and risk. *Land Economics*, 84(3):434–448.

Bolitzer, B. and Netusil, N. R. (2000). The impact of open spaces on property values in portland, oregon. *Journal of Environmental Management*, 59(3):185–193.

Brasington, D. and Haurin, D. R. (2006). Educational outcomes and house values: A test of the value added approach. *Journal of Regional Science*, 46(2):245–268.

Brown, J. P., Florax, R. J., and McNamara, K. T. (2009). Determinants of investment flows in US manufacturing. *Review of Regional Studies*, 39(3):269–286.

Cebula, R. J. (2009). The hedonic pricing model applied to the housing market of the city of Savannah and its Savannah Historic Landmark District. *Review of Regional Studies*, 39(1):9–22.

Clapp, J. M., Nanda, A., and Ross, S. L. (2008). Which school attributes matter? The influence of school district performance and demographic composition on property values. *Journal of Urban Economics*, 63(2):451–466.

Cohen, J. P. and Coughlin, C. C. (2008). *Changing noise levels and housing prices near the Atlanta airport*. Federal Reserve Bank of St. Louis. Working Paper 2005-060D.

Conway, D., Li, C. Q., Wolch, J., Kahle, C., and Jerrett, M. (2010). A spatial autocorrelation approach for examining the effects of urban greenspace on residential property values. *The Journal of Real Estate Finance and Economics*, 41(2):150–169.

Correll, M. R., Lillydahl, J. H., and Singell, L. D. (1978). The effects of greenbelts on residential property values: Some findings on the political economy of open space. *Land economics*, 54(2):207–217.

Cotteleer, G. and van Kooten, G. C. (2012). Expert opinion versus actual transaction evidence in the valuation of non-market amenities. *Economic Modeling*, 29(1):32–40.

Crompton, J. L. (2001). The impact of parks on property values: A review of the empirical evidence. *Journal of Leisure Research*, 33(1):1–31.

Crompton, J. L. (2004). *The Impact of Parks and Open Space on Property Values and the Property Tax Base*. National Recreation & Park Association, Ashburn, VA.

Crompton, J. L. (2005). The impact of parks on property values: Empirical evidence from the past two decades in the United States. *Managing Leisure*, 10(4):203–218.

Czembrowski, P. and Kronenberg, J. (2016). Hedonic pricing and different urban green space types and sizes: Insights into the discussion on valuing ecosystem services. *Landscape and Urban Planning*, 146:11–19.

Deaton, B. J. and Hoehn, J. P. (2004). Hedonic analysis of hazardous waste sites in the presence of other urban disamenities. *Environmental Science & Policy*, 7(6):499–508.

Doss, C. R. and Taff, S. J. (1996). The influence of wetland type and wetland proximity on residential property values. *Journal of Agricultural and Resource Economics*, 21(1):120–129.

Dougherty, J., Harrelson, J., Maloney, L., Murphy, D., Smith, R., Snow, M., and Zannoni, D. (2009). School choice in suburbia: Test scores, race, and housing markets. *American Journal of Education*, 115(4):523–548.

du Preez, M. and Sale, M. (2014). Municipal assessments versus actual sales price information in hedonic price studies: A South African case. *Economic Research Southern Africa*. Working Paper 441.

Eiser, J. R., Stafford, T., Henneberry, J., and Catney, P. (2007). Risk perception and trust in the context of urban brownfields. *Environmental Hazards*, 7(2):150–156.

Espey, M. and Owusu-Edusei, K. (2001). Neighborhood parks and residential property values in Greenville, South Carolina. *Journal of Agricultural and Applied Economics*, 33(3):487–492.

Freeman, A. M., Herriges, J. A., and Kling, C. L. (2003). *The Measurement of Environmental and Resource Values: Theory and Methods*. Resources for the Future, Washington, DC, 3 edition.

Geoghegan, J. (2002). The value of open spaces in residential land use. *Land Use Policy*, 19(1):91–98.

Hess, D. B. and Almeida, T. M. (2007). Impact of proximity to light rail rapid transit on station-area property values in Buffalo, New York. *Urban Studies*, 44(5-6):1041–1068.

Ihlanfeldt, K. R. and Taylor, L. O. (2002). Assessing the impacts of environmental contamination on commercial and industrial properties. In *World Congress of Environmental and Resource Economists*. Monterey, California.

Irwin, E. G. (2002). The effects of open space on residential property values. *Land Economics*, 78(4):465–480.

Izón, G. M., Hand, M. S., Fontenla, M., and Berrens, R. P. (2010). The economic value of protecting inventoried roadless areas: A spatial hedonic price study in New Mexico. *Contemporary Economic Policy*, 28(4):537–553.

Jim, C. and Chen, W. Y. (2010). External effects of neighbourhood parks and landscape elements on high-rise residential value. *Land Use Policy*, 27(2):662–670.

Kong, F., Yin, H., and Nakagoshi, N. (2007). Using gis and landscape metrics in the hedonic price modeling of the amenity value of urban green space: A case study in Jinan City, China. *Landscape and urban planning*, 79(3-4):240–252.

Kovacs, K. F. (2012). Integrating property value and local recreation models to value ecosystem services from regional parks. *Landscape and Urban Planning*, 108(2-4):79–90.

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy*, 74(2):132–157.

Landry, C. E. and Hindsley, P. (2011). Valuing beach quality with hedonic property models. *Land Economics*, 87(1):92–108.

Leigh, N. G. and Coffin, S. L. (2005). Modeling the relationship among brownfields, property values, and community revitalization. *Housing Policy Debate*, 16(2):257–280.

LeSage, J. (2014). What regional scientists need to know about spatial econometrics. *Review of Regional Studies*, 44(1):13–32.

LeSage, J. and Pace, R. K. (2008). *Introduction to spatial econometrics*. Revue d'Economie Industrielle, Nice, FR.

LeSage, J. P. (1999). *Applied econometrics using MATLAB*. University of Toledo Department of Economics, Toledo, OH.

LeSage, J. P. and Ha, C. L. (2012). The impact of migration on social capital: Do migrants take their bowling balls with them? *Growth and Change*, 43(1):1–26.

LeSage, J. P. and Pace, R. K. (2014). Interpreting spatial econometric models. In *Handbook of Regional Science*, pages 1535–1552. Springer, New York, NY.

Lin, I.-H., Wu, C., and De Sousa, C. (2013). Examining the economic impact of park facilities on neighboring residential property values. *Applied Geography*, 45:322–331.

Lutzenhiser, M. and Netusil, N. R. (2001). The effect of open spaces on a home's sale price. *Contemporary Economic Policy*, 19(3):291–298.

Lynch, A. K. and Rasmussen, D. W. (2001). Measuring the impact of crime on house prices. *Applied Economics*, 33(15):1981–1989.

Maslianskaïa-Pautrel, M. (2016). The nature and impacts of environmental spillovers on housing prices: A spatial hedonic analysis. FAERE Working Paper 2016.04.

McCord, J., McCord, M., McCluskey, W., Davis, P., McIlhatton, D., and Haran, M. (2014). Effect of public green space on residential property values in Belfast metropolitan area. *Journal of Financial Management of Property and Construction*, 19(2):117–137.

Mihaescu, O. and vom Hofe, R. (2013). Using spatial regression to estimate property tax discounts from proximity to brownfields: A tool for local policy-making. *Journal of Environmental Assessment Policy and Management*, 15(1).

Newell, G. F. (1980). *Traffic Flow on Transportation Networks*. MIT Press, Cambridge, MA.

Nicholls, S. (2004). Measuring the impact of parks on property values: New research shows that green spaces increase the value of nearby housing. *Parks and Recreation*, 39(3):24–32.

Nicholls, S. and Crompton, J. L. (2005). The impact of greenways on property values: Evidence from Austin, Texas. *Journal of Leisure Research*, 37(3):321–341.

O'Sullivan, S. and Morrall, J. (1996). Walking distances to and from light-rail transit stations. *Journal of the Transportation Research Board*, 1538(1):19–26.

Parent, O. and vom Hofe, R. (2013). Understanding the impact of trails on residential property values in the presence of spatial dependence. *Annals of Regional Science*, 51(2):355–375.

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

Ross, J. M., Farmer, M. C., and Lipscomb, C. A. (2011). Inconsistency in welfare inferences from distance variables in hedonic regressions. *Journal of Real Estate Finance and Economics*, 43(3):385–400.

Sander, H., Polasky, S., and Haight, R. G. (2010a). The value of urban tree cover: A hedonic property price model in Ramsey and Dakota Counties, Minnesota, USA. *Ecological Economics*, 69(8):1646–1656.

Sander, H. A., Ghosh, D., van Riper, D., and Manson, S. M. (2010b). How do you measure distance in spatial models? An example using open-space valuation. *Environment and Planning B: Planning and Design*, 37(5):874–894.

Shultz, S. D. and King, D. A. (2001). The use of census data for hedonic price estimates of open-space amenities and land use. *Journal of Real Estate Finance and Economics*, 22(2-3):239–252.

Svetlik, J. B. (2007). *Externality effects of local brownfields on residential property values.* Business of Brownfields Conference, Pittsburgh, PA.

Troy, A. and Grove, J. M. (2008). Property values, parks, and crime: A hedonic analysis in Baltimore, MD. *Landscape and Urban Planning*, 87(3):233–245.

Ventolo, W. L. and Williams, M. R. (1994). *Fundamentals of real estate appraisal.* Dearborn Real Estate, Dearborn MI.