Open Space, Residential Property Values, and Spatial Context

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Abstract

We use hedonic analysis of home transaction data from the Minneapolis-St. Paul metropolitan area to estimate the effects of proximity to open space on sales price. Importantly, we allow the effects of proximity to vary spatially with many covariates, such as population density and neighborhood income. We find that the amenity effect of proximity to open space is larger in dense, high crime, high income neighborhoods near the central business district and that sample mean effects may misrepresent substantially the amenity effect of open space in particular neighborhoods. Our results suggest that planners and developers need to consider spatial context when providing or protecting open space amenities.

Key Words: Open Space, Hedonic, Fixed Effects, Geographic Information Systems (GIS)

JEL Classification Numbers: Q15; Q21; Q26

1. Introduction

Rapid urban expansion and related increases in vehicle travel may have many adverse effects, including air and water pollution, noise and congestion, and the loss of open space and wildlife habitat. The Environmental Protection Agency (EPA) and some metropolitan area commissions have championed "smart growth"—compact and mixed development coupled with the conservation of open space and ecological land use resources, such as parks and natural areas—to mitigate these effects (EPA 2001). In order to make appropriate decisions regarding the provision of open space and design more effective smart-growth policies, growing cities need information regarding the value of open areas. Such information may also help real estate developers plan more desirable residential communities and profit by limiting development (Heal 2001).

In this paper we estimate the amenity value of open space and consider how it varies spatially. We use hedonic analysis of home transaction data from the Minneapolis-St. Paul metropolitan area (Twin Cities) to estimate the effects on home value of proximity to neighborhood parks, regional, state, and federal parks and natural areas (henceforth defined as special parks), golf courses, and cemeteries. We use geographic information systems (GIS) software to derive these proximity measures from regional land use data. Importantly, we allow the effects of proximity to vary with amenity size, population density, income, and other covariates believed to influence the demand for open space. In addition to controlling for home structural attributes and other environmental amenities, we include local fixed effects to control for neighborhood characteristics, geographic location, and omitted spatial variables.

Open space may provide a number of benefits, including opportunities for recreation, fitness, and education. In a residential context, open space may also provide privacy, pleasing views, or simply the absence of negative externalities associated with development (Irwin 2002). In a competitive housing market prospective homebuyers will bid up the prices of homes near open space in order to gain these benefits, and the externalities generated by proximity to open space will be capitalized into residential property values. Open space may also provide various ecological benefits, such as wildlife habitat or improved water quality, that are not likely to be reflected in property values.

A large and growing literature estimates the effects of open space on residential property values. [1] Some recent studies measure the distance to nearby open areas and distinguish between specific land use types (Bolitzer and Netusil 2000, Lutzenhiser and Netusil 2001, Smith et al. 2002). In general these studies find that home value increases with proximity to open space and that the effect varies by type. Additionally, Bolitzer and Netusil (2000) and Lutzenhiser and Netusil (2001) find that home value increases with the size of nearby open areas. Other recent studies measure the total quantity of surrounding open space and distinguish broadly between protected open space, such as public parks and land under conservation easement, and developable open space, such as privately owned agricultural land (Irwin and Bockstael 2001, Irwin 2002, Geoghegan 2002, Geoghegan et al. 2003). This distinction is relevant since the effect of open space on home value reflects both current and expected future amenities. In general these studies find that preserved open space increases home value while developable open space has a lesser, insignificant, or negative effect on home value. Cheshire and Sheppard (1995) find that the quantity of publicly accessible open space surrounding a home has a larger positive effect on home

[1] A number of studies use hedonic analysis to estimate the amenity value of particular types of open space, such as golf courses (Do and Grudnitski 1995), neighborhood parks (Weicher and Zerbst 1973, Espey and Owusu-Edusei 2001), greenbelts (Correll et al. 1978, Lee and Linneman 1998), forest areas (Tyrvainen and Miettinen 2000), and wetlands (Doss and Taff 1996, Mahan et al. 2000, Earnhart 2001). Other studies use alternative methods: Schultz and King (2001) use aggregate census data to estimate the effects of open space on average home values; Breffle et al. (1998) employ survey methods to estimate the willingness to pay to preserve undeveloped land; Riddel (2001) models the dynamic effects of an open space purchase on housing and labor markets. See McConnell and Walls (2005) for a comprehensive survey of open space valuation studies that use stated preference and property value methods.

value than inaccessible open space. Our paper is similar to the first set of studies in that we estimate the effects of proximity to several specific types of preserved open space on home value.

Few hedonic studies consider the possibility that the effects of open space on property values vary spatially within a single housing market. Geoghegan et al. (1997) find that the amenity effect of open space first increases and then falls with distance to the CBD, while Acharya and Bennett (2001) find that the effect of surrounding land use patterns on home value depends on population density. Geoghegan et al. (2003) estimate separate hedonic functions for the three counties in their study area. They find that the effects of open space on home value differ by county and speculate that these differences may be related to variation in county income levels and quantities of open space. Cheshire and Sheppard (1998) use implied marginal prices from their first stage hedonic equation to estimate demand for accessible and inaccessible open space. They find that demand for both types of open space increases with income.[2]

A number of studies in the local public goods literature also suggest that amenity values for open space may vary spatially. Several studies use government expenditure data to estimate voter demand for parks (Bergstrom and Goodman 1973, Borcherding and Deacon 1972, Pack and Pack 1978, Perkins 1977, Santerre 1985). These studies find that spending on parks is positively related to income. Additionally, Santerre (1985) finds that spending decreases with distance to the central business district (CBD), while Bergstrom and Goodman (1973) find evidence that spending increases with population density and age. Bates and Santerre (2001) use land use data to estimate voter demand for locally owned public open space. They find that the quantity of open space demanded increases with income. Interestingly, they find

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[2] In an extension they find that accessible open space disproportionately benefits households with lower incomes while inaccessible open space disproportionately benefits wealthier households (Cheshire and Sheppard 2002).

that privately owned open space, such as golf courses or preserved farmland, is not a good substitute for public open space.[3] They do not estimate the effect of private lot sizes on demand.

This paper contributes to the existing literature by exploring systematically how the effect of open space on home value varies spatially. We consider how the effect of proximity to open space on sales price varies with amenity size, private lot size, population density, proximity to the CBD, income levels, crime rates, and neighborhood age composition. Geoghegan et al. (1997) and Acharya and Bennett (2001) are the only comparable studies we are aware of, and these studies only consider the effect of a single covariate. Cheshire and Sheppard (1998) estimate demand but also consider fewer covariates. Additionally, we are aware of only two previous open space studies that control for neighborhood characteristics and omitted variables with a large number of local fixed effects (Do and Grudnitski 1995, Espey and Owusu-Edusei 2001), though our sample area and dataset are substantially larger, and our fixed effects are given at a finer geographic scale.[4] This is a useful innovation given the likelihood of correlated omitted variables in hedonic open space studies.

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[3] Bates and Santerre (2001) posit two reasons for the lack of substitutability between public and private open space. First, most privately-owned open space is not protected from development. Second, even if private open space remains undeveloped it may not be made available for public use. This interpretation is generally consistent with the results of hedonic studies that consider this issue (Cheshire and Sheppard 1995, Irwin and Bockstael 2001, Irwin 2002, Geoghegan 2002, Geoghegan et al. 2003).

[4] We control for approximately 1,800 block group fixed effects, while Espey and Owusu-Edusei (2001) control for 28 census tract fixed effects and Do and Grudnitski (1995) control for 12 grid areas that are 1 km square. The census tracts in our sample contain 3.5 block groups on average; the average block group size for homes in the central city is about 0.6 square km. Several other studies we survey here control for unobserved spatial heterogeneity on a larger geographic scale with a handful of dummy variables.

We find that the sales price of an average home increases with proximity to neighborhood parks, special parks, and golf courses. By contrast, the sales price of an average home decreases with proximity to cemeteries, though our estimate of this coefficient is less precise. These results are sensitive to the inclusion of local fixed effects: when we replace our fixed effects with a large number of observable control variables we find that home value decreases with proximity to neighborhood parks.

We find that the amenity effect of proximity to neighborhood parks is higher in neighborhoods with more children and rises with population density, proximity to the CBD, income levels, and crime rates. Surprisingly, the amenity effect of proximity to neighborhood parks falls with park size, though the difference is small. The amenity effect of proximity to special parks falls with distance to the CBD and the fraction of the population under age 18 and rises with population density, income levels, and crime rates. Interestingly, our estimates suggest that the amenity effect of proximity to special parks is higher for homes with large private lots. The amenity effect of proximity to golf courses falls with population density, income, and distance to the CBD, while the amenity effect of proximity to cemeteries falls with private lot sizes. These spatial considerations are of paramount importance, as average effects may misrepresent substantially the effect of open space on home values in particular neighborhoods. In the case of neighborhood parks, the average effect understates the effect of proximity by up to a factor of 12 and overstates it by up to a factor of 10. Similarly, in the case of special parks the average effect understates the effect of proximity by up to a factor of 17 and understates it by up to a factor of 2.

The remainder of this paper is divided into four sections. Section 1 discusses our econometric model. Section 2 describes our data sources and provides descriptive statistics. Section 3 presents the results of our econometric estimation. Section 4 concludes.

2. Econometric Model

Using standard hedonic theory (Rosen 1974) we define a home h by its structural attributes S_h, neighborhood characteristics and location N_h, and environmental amenities A_h. Given an existing stock of homes, and assuming a competitive housing market, individual homebuyers maximize utility by trading off the quantities of housing attributes associated with particular locations for changes in price. By this process homebuyers are matched with homes such that they cannot achieve a higher utility by choosing a different location. This leads to an equilibrium hedonic price function, which relates the market price of a home P_h to its attributes:

$$P_h = P(S_h, N_h, A_h). \tag{1}$$

Differentiation of the hedonic price function with respect to a particular attribute yields the marginal implicit price of that attribute, which equals the homebuyer's marginal willingness to pay in equilibrium.[5]

Econometric specification and estimation of the hedonic price function poses a number of potential problems. Irwin and Bockstael (2001) formalize two specific problems associated with the identification of amenity values for open space. First, the quantity of privately owned, developable open space that surrounds a home is endogenous to home value due to spillovers among proximate parcels of land. This issue is not of great concern here since most of the parks, golf courses, and cemeteries in our sample are publicly owned and exist in a more or less permanent state. Indeed, previous studies designate these areas as preserved open space. Second, omitted spatial variables that affect home value are necessarily correlated with the surrounding quantity of open space since property values drive development. This is true even for public open space; indeed, Bates and Santerre (2001) show that public

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[5] Estimation of the hedonic price function alone does not reveal the entire willingness to pay function for housing characteristics. Rosen (1974) suggests a second-stage analysis, wherein estimated marginal implicit prices are regressed on a vector of demand variables to identify willingness to pay. We do not undertake such an analysis here, though Palmquist (1992) shows that the first stage sufficiently measures total benefits in the case of localized externalities that affect a small number of people. Several open space studies undertake a second-stage analysis and estimate demand (Garrod and Willis 1992, Cheshire and Sheppard 1998, Cheshire and Sheppard 2002). See Palmquist (1991), Sheppard (1999), and Freeman (2003) for surveys of hedonic theory and methods.

provision depends on private land values. Therefore, any historical factors that continue to affect property values will be correlated with the existing open space amenities in our sample and omitting these factors will cause OLS estimates to be biased. Several studies use an instrumental variables approach to deal with these sources of bias (Irwin and Bockstael 2001, Irwin 2002, Geoghegan et al. 2003). We control for potential omitted spatial variables through the use of local fixed effects.

Theory has little to say about the functional form of the hedonic equation. Graphical inspection of the relationship between home sales price and key explanatory variables in our dataset, such as the square footage of a home, clearly suggests a log-log functional form. We try estimating flexible-form models with Box-Cox transformations of the dependent and independent variables but are unable to reject a log-log relationship. We therefore estimate a hedonic equation of the following form:

$$\ln P_{hi} = \alpha_X{}'\ln X_{hi} + \alpha_Y{}'Y_{hi} + \sum_{a\in A} \ln d_{a,hi}(\beta_a + \theta_a s_{a,hi} + \gamma_a{}'Z_{hi}) + \delta_i + \varepsilon_{hi}, \qquad (2)$$

where:

P_{hi} = sales price of home h in block group i,

X_{hi} = continuous home structural characteristics,

Y_{hi} = dichotomous home structural characteristics and month dummies,

α_X and α_Y = parameter vectors to be estimated,

$d_{a,hi}$ = distance from home to nearest amenity of type a,

$s_{a,hi}$ = size of nearest amenity of type a,

Z_{hi} = covariates interacted with amenity distance,

β_a, θ_a, and γ_a = two parameters and parameter vector to be estimated for each a,

δ_i = block group fixed effect, and

ε_{hi} = random error term.

We can interpret each coefficient in α_X directly as the elasticity of sales price with respect to the corresponding continuous home structure variable, as long as the variable does not appear in Z_{hi}. The elasticity of sales price with respect to distance to amenity type a is given by:

$$\frac{\partial \ln P_{hi}}{\partial \ln d_{a,hi}} = \beta_a + \theta_a s_{a,hi} + \gamma_a{}' Z_{hi}. \qquad (3)$$

When this elasticity is negative home value decreases with distance; that is, home value increases with proximity. The innovation here is that we allow this elasticity to vary with amenity size $s_{a,hi}$ and covariate vector Z_{hi}, which includes amenity size, population density, income, and other variables expected to influence demand for open space. We enter these covariates linearly.[6] When an element of γ_a is negative then an increase in the corresponding element of $Z_{a,hi}$ increases the amenity effect of proximity to amenity a.

Previous studies find that neighborhood characteristics, such as income levels and distance to the CBD, have a direct effect on home value. We control for the direct effects of neighborhood characteristics and potential omitted spatial variables through the use of census block group fixed effects. These fixed effects are not a panacea, however. First, our designation of block groups as neighborhoods is somewhat arbitrary. If block groups overlap perceived neighborhood boundaries then omitted variables may persist. On the other hand, if block groups are nested within perceived neighborhoods then our estimates may be inefficient.[7] Second, our fixed effects may fail to control for omitted variables that affect only a small

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[6] Linear covariates perform better than logged covariates. We also estimate models where the elasticity is quadratic in the covariates, but our conclusions about the directional effects of the covariate variables are unchanged.

[7] Gibbons and Machin (2003) avoid this issue to some extent by using a distance-weighted smoothing function to control for spatial effects prior to estimation. This approach allows them greater flexibility in the modeling of spatial effects, though it still requires assumptions with regard to the choice of smoothing function and its parameters.

number of properties. Lastly, although our fixed effects control for unobserved heterogeneity in overall home value they do not control for unobserved covariates that determine the spatial variation of amenity distance effects. This implies that our covariate interactions may be subject to omitted variables bias. We interact our measures of amenity distance with county dummy variables in an attempt to control for omitted variables but subsequently are unable to estimate the covariate interactions with precision.

Note that our proxy measures of distance to the nearest open space amenities may fail to account for other, potentially more important open areas that are near a home but not nearest. Indeed, a number of recent studies measure the total quantity of open space that surrounds a home within a given distance (Cheshire and Sheppard 1995, Irwin and Bockstael 2001, Irwin 2002, Geoghegan 2002) or at multiple scales (Acharya and Bennett 2001, Geoghegan et al. 1997, Geoghegan 2003). Several studies justify this specification with the assumption that homeowners care about the overall pattern of land use that surrounds their home. For homes in the same census block group, however, the overall pattern of land use is often the same. Therefore, given our inclusion of local fixed effects, distance to the nearest open space is a reasonable proxy.

3. Data

Table 1 lists the variables that we use to estimate equation (2), while table 2 presents descriptive statistics for the data in our estimation sample.

These data come from several sources. Our home transactions data come from Regional Multiple Listing Service of Minnesota, Inc. and represent all 30,104 single-family home transactions in their database for the Twin Cities during 1997. We locate these homes using GIS address data from The

Lawrence Group (TLG).[8] We focus on transactions within urbanized areas of the Twin Cities in an effort to minimize possible complications associated with large tracts of privately owned, undeveloped land (Irwin and Bockstael 2001).[9] This sample represents 27,336 home transactions. We omit approximately 9% of these observations because of missing or implausible data, which reduces our estimation sample to 24,862 transactions.[10]

We compute the age of each home in 1997 based on its year of construction. We derive lot sizes for most homes by multiplying lot length by lot width, though some transaction records provide acreage values directly. For observations with irregularly shaped lots we estimate acreage using the lot dimensions provided. We also include dummy variables for the month of sale to control for potential seasonality in housing prices.

The neighborhood covariates come from a variety of sources. Using TLG address data we locate the CBD of Minneapolis and the CBD of St. Paul and calculate the distance from each home to the nearest CBD. Our population density, median income, and age composition variables come from 1990 U.S. Census block group data. We obtain crime data for Minneapolis and St. Paul city neighborhoods from the Minneapolis and St. Paul police departments and crime data for suburban municipalities from

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[8] We are unable to locate approximately 2% of homes due to missing or inaccurate address information. These homes tend to be located in municipalities on the periphery of the urbanized area where address information is presumably less complete.

[9] We define urbanized areas as the 1998 Metropolitan Urban Services Area, for which the Metropolitan Council provides water, sewer, and other urban services.

[10] Of these omitted observations approximately 80% had missing lot size data, 17% had missing or implausibly low square footage, 6% had missing age data, 2% had missing bathrooms data, and less than 1% had missing sales price, crime, or census demographic data. These percentages sum to over 100% since some observations lacked data for more than one variable. We also omit two observations with lot sizes of approximately 300 and 1,000 acres.

the Minnesota Department of Public Safety. These data record the number of serious crimes, such as thefts and assaults, that were reported during 2000 for each city neighborhood and suburban municipality. We use these data and 2000 U.S. Census population data to calculate the crime rate for each city neighborhood and suburban municipality.[11]

Finally, we derive our open space variables from 2001 TLG land use data, which record the sizes and locations of 2,174 open spaces, including 1,825 neighborhood parks, 153 golf courses, 152 special parks, and 44 cemeteries. We define special parks as national, state, and regional parks, arboretums, nature centers, natural areas, and wildlife refuges, distinguishing these areas from neighborhood parks, which are generally more developed and provide fewer natural amenities and wildlife habitat. We use these data to calculate the distance from each home to the nearest open area of each type, as well as the distance to the nearest lake and major river.[12] In addition to these measures of proximity, we record the sizes of the nearest neighborhood park, special park, golf course, cemetery, and lake. Although our home transaction data are from 1997, the high cost associated with changing from one land use to another makes 2001 land use a good proxy for 1997 land use (Smith et al. 2002).

We expect sales price to increase in all home structure characteristics except age. We expect sales price to increase with proximity to open space and environmental amenities. However, we also expect these effects to vary spatially. Specifically, we predict that the amenity effect of proximity to open space will increase with amenity size, neighborhood income, population density, and the proportion of children and

[11] We obtain census population data for Minneapolis and St. Paul indirectly from the City of Minneapolis and the Wilder Research Center, respectively, since these organizations provide U.S. Census block group data aggregated by city neighborhood.

[12] A small number of homes were originally 0m from a park, golf course, cemetery, lake or river. We add 1m to all distance measures prior to logarithmic conversion to avoid unnecessary missing values.

elderly. We predict that the amenity effect of proximity will decrease with private lot size, crime rates, and distance to the CBD.

4. Estimation and results

In order to simplify interpretation of our amenity coefficients we normalize the vector of covariates Z_{hi} prior to estimation according to the following linear transformation:

$$Z_{hi}^* = {(Z_{hi} - \bar{Z})} \big/ {\bar{Z}}, \qquad (5)$$

where $\bar{Z} = \sum_i \sum_h Z_{hi} \big/ N$ and N is the total number of observations in the dataset. So Z_{hi}^* is simply the percent deviation of covariate Z_{hi} from its sample mean. We normalize the amenity size variables analogously. We then estimate equation (2) using the standard fixed effects estimator, which takes the difference of each variable from its block group mean and then applies OLS. Table 3 presents the results of this estimation.

The coefficients for the home structure variables are all estimated precisely with the expected signs and reasonable magnitudes. Sales price increases by about 0.50 percent for every one percent increase in square footage, 0.08 percent for every one percent increase in the number of bathrooms, and 5 percent with the addition of a fireplace.[13] Sales price decreases by about 0.13 percent for every one percent increase in the age of a home. Finally, sales price increases by about 0.09 percent for every one percent increase in lot size, assuming the home has average amenity characteristics.[14]

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[13] The estimated percent effect of a fireplace on sales price is $\eta' = e^{\{\eta - V(\eta)/2\}} - 1$, where η is the estimated coefficient and $V(\eta)$ is its estimated variance (Halvorsen and Palmquist 1980, Kennedy 1981).

[14] The effect of lot size depends on amenity distance since lot size appears in the covariate vector Z_{hi}.

We now turn to the amenity coefficients. Given our normalization of the covariates the elasticity in equation (3) becomes:

$$\frac{\partial \ln P_{hi}}{\partial \ln d_{a,hi}} = \beta_a + \theta_a s_{a,hi}* + \gamma_a' Z_{hi}*, \tag{6}$$

which simplifies to

$$\frac{\partial \ln P_{hi}}{\partial \ln d_{a,hi}} = \beta_a \tag{7}$$

for a home with average covariate characteristics. Therefore, we can interpret the amenity distance coefficients in table 3 directly as the elasticity of sales price with respect to amenity distance for an amenity of average size and a home with average covariate characteristics. These coefficients imply that sales price increases by about 0.0035 percent for every one percent decrease in the distance to the nearest neighborhood park, 0.0252 percent for every one percent decrease in the distance to the nearest special park, 0.0060 percent for every one percent decrease in the distance to the nearest golf course, 0.0342 percent for every one percent decrease in the distance to the nearest lake, and 0.0273 percent for every one percent decrease in the distance to the nearest major river. Sales price decreases by about 0.0084 percent for every one percent decrease in the distance to the nearest cemetery, though this coefficient is not estimated precisely.

We now discuss how these effects vary spatially. Surprisingly, the amenity effect of proximity to neighborhood parks falls with park size, though the difference is small and may be caused by some omitted disamenity that is correlated with large parks, such as noise or traffic flow. As expected, the amenity effect of proximity to neighborhood parks falls with distance to the CBD and rises with density, income, and the fraction of the population under age 18. Surprisingly, the amenity effect of proximity to neighborhood parks rises with crime rates, indicating that neighborhood parks may act as buffers against the negative effects of crime. Figure 1 provides a sense of the magnitudes of these effects.

As expected, the amenity effect of proximity to special parks falls with distance to the CBD and rises with park size, density, and income. As with neighborhood parks the amenity effect of proximity to special parks rises with crime rates. The amenity effect of proximity to special parks falls with the fraction of the population under age 18, suggesting that the middle aged benefit from special parks more than the young. Surprisingly, the amenity effect of proximity to special parks rises with private lot sizes, indicating that special parks and large private lots are complements. Parsons (1990) provides an alternative explanation by demonstrating that the price per acre of land must be independent of lot size in equilibrium. This implies that purchasers of large lots pay for both the amenity benefits they receive as well as the amenity benefits that would have accrued to additional homeowners were the lot subdivided further. We pursue this issue further but are unable to determine conclusively the reason for this unexpected result. [15] Figure 2 provides a sense of the magnitudes of these effects.

The effects of golf courses, cemeteries, lakes, and rivers also vary spatially. The amenity effect of proximity to golf courses decreases with distance to the CBD, the fraction of the population age 65 and older, and density, perhaps due to congestion. Surprisingly, the amenity effect of proximity to golf

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[15] Following Parsons (1990) we scale our amenity measures by lot size. After scaling we find that the amenity value of special parks decreases with lot size, as expected, but that few other covariate interactions are significant and that home value actually decreases with proximity to special parks and golf courses. Alternatively, Parsons (1990) points out that the cost of changing lot size in developed neighborhoods may be prohibitively high in practice. Following this logic we assume that the cost of subdivision is lowest for homes with large lots and try dropping homes with large lots from our sample. The negative coefficient for the lot size covariate interaction for special parks eventually becomes insignificant, but it is unclear whether this reflects prohibitively high subdivision costs or simply a reduced sample size. Finally, we replace the lot size covariate with block group average lot size. Interestingly, we find that the amenity value of proximity to neighborhood parks decreases with average lot sizes, though this effect is only statistically significant at the 16% level. We continue to find that the amenity value of proximity to special parks increases with lot size.

courses decreases with income. We do not have a good explanation for this result. The amenity effect of proximity to cemeteries decreases with private lot sizes. Surprisingly, the amenity effect of proximity to lakes decreases with lake size, though large lakes may also be associated with more and noisier watercraft activity. The amenity effect of proximity to lakes increases with lot size, distance to the CBD, income, and the fraction of the population age 65 and older and decreases with crime rates and the fraction of the population under age 18. Finally, the amenity effect of proximity to rivers falls with private lot sizes and the fraction of the population under age 18 and rises with income.

Using equation (6) and the coefficient estimates in table 3 we calculate for each home the elasticity of sales price with respect to neighborhood parks and special parks. Figure 3 shows the distributions of these elasticity effects. The average elasticity of sales price with respect to amenity distance is -0.0035 for neighborhood parks and -0.0260 for special parks. These results are consistent with the coefficient estimates for amenity distance in table 3. Average effects may substantially misrepresent amenity effects in particular neighborhoods, however. The elasticity of sales price with respect to the distance to the nearest neighborhood park ranges from -0.0424 to 0.03112 in our sample, implying that the average elasticity understates the positive effects of proximity by up to a factor of 12 and overstates them by up to a factor of 10. Similarly, the elasticity of sales price with respect to the distance to the nearest special park ranges from -0.4335 to 0.0240 in our sample, implying that the average elasticity understates the positive effects of proximity by up to a factor of 17 and overstates them by up to a factor of 2.

We also estimate equation (2) with a large number of neighborhood control variables in place of the block group fixed effects.[16] Although we estimate the amenity distance coefficients with increased

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[16] We include controls for the direct effects on sales price of income, density, racial composition, age composition, home ownership rates, distance to the nearest CBD, school quality, crime rates, distance to major highways, and distance to major shopping centers.

precision, we find that that the value of a home with average covariate characteristics decreases with proximity to neighborhood parks. Likewise, we estimate the covariate interactions with increased precision, but many of the coefficient estimates switch to having unexpected signs. These results suggest that it is important to control explicitly for omitted spatial variables in hedonic open space studies that use data from complex urban housing markets.

5. Conclusion

In this paper we use hedonic analysis of home transaction data from the Twin Cities to estimate the effect of proximity to open space on sales prices. We consider several types of open space, including neighborhood parks, special parks, golf courses, and cemeteries. Importantly, we allow the effects of proximity to vary with population density, income, and other covariates believed to influence the demand for open space amenities. Finally, we control for neighborhood characteristics and potential omitted spatial variables through the use of local fixed effects.

There are several limitations to our methodological approach. First, we do not consider other types of open space, such as vacant lots or university campuses, that may confer certain open space benefits, nor do we consider potentially relevant distinctions within our broad classifications. Second, our proxy for open space may fail to account for important amenities that are close to a home but not closest. Third, our block group fixed effects may not correspond to perceived residential neighborhoods and do not control for omitted variables that affect a small number of properties. Fourth, our estimates reflect only the marginal value of open space and not the entire willingness to pay function. Finally, our estimates measure the amenity value of open space in a residential setting and do not capture many of the ecological and public good benefits that open areas provide.

Nonetheless, our results yield two important insights. First, the effect of open space on property values depends on spatial context. Broadly speaking, proximity to open space is valued highly by urban residents living in dense neighborhoods near the CBD; suburban residents do not appear to value proximity to open space as highly. Therefore, results from studies that focus on city preferences should not necessarily be used to draw implications for suburban planning. The effect of open space on home values in particular neighborhoods will further depend on income levels, age composition, crime rates, and potentially other neighborhood characteristics. Second, unobserved neighborhood characteristics, if uncontrolled for, can lead to biased estimates for observed characteristics. For example, in the absence of local fixed effects we find that home value falls with proximity to neighborhood parks.

Our results suggest that urban planners and developers need to think about spatial context when providing or protecting open space amenities. From a homeowners perspective, neighorhood parks are more highly valued in dense, high crime neighborhoods near the CBD by families with children. Special parks are more highly valued in dense, high crime neighborhoods by the middle aged. High income households exhibit greater marginal willingness to pay for both types of open space, and there is some evidence that these values depend on private lot sizes.

References

Acharya, Gayatri and Lynne L. Bennett. (2001). "Valuing Open Space and Land-Use Patterns in Urban Watersheds." Journal of Real Estate Finance and Economics, 22 (2): 221 – 237.

Bates, Laurie J. and Rexford E. Santerre. (2001). "The Public Demand for Open Space: The Case of Connecticut Communities." Journal of Urban Economics, 50 (1): 97 – 111.

Bergstrom, Theodore C. and Robert P. Goodman. (1973). "Private Demands for Public Goods." American Economic Review, 63 (3): 280 – 296.

Bolitzer, Benjamin and Noelwah R. Netusil. (2000). "The Impact of Open Spaces on Property Values in Portland, Oregon." Journal of Environmental Management, 59 (3): 185 – 193.

Borcherding, Thomas E. and Robert T. Deacon. (1972). "The Demand for Services of Non-Federal Governments." American Economic Review, 62 (5): 891 – 901.

Breffle, William S., Edward R. Morey, and Tymon S. Lodder. (1998). "Using Contingent Valuation to Estimate a Neighborhood's Willingness to Pay for Undeveloped Urban Land." Urban Studies, 35 (4): 715 – 727.

Cheshire, Paul C. and Stephen C. Sheppard. (1995). "On the Price of Land and the Value of Amenities." Economica, 62 (127): 247 – 267.

Cheshire, Paul C. and Stephen C. Sheppard. (1998). "Estimating the Demand for Housing, Land, and Neighbourhood Characteristics." Oxford Bulletin of Economics and Statistics, 60 (3): 357 – 382.

Cheshire, Paul C. and Stephen C. Sheppard. (2002). "The Welfare Economics of Land Use Planning." Journal of Urban Economics, 52 (2): 242 – 269.

Correll, Mark R., Jane H. Lillydahl and Larry D. Singell. (1978). "The Effects of Greenbelts on Residential Property Values: Some Findings on the Political Economy of Open Space." Land Economics, Vol. 54 (2): 207 – 217.

Do, A. Quang and Gary Grudnitski. (1995). “Golf Courses and Residential House Prices: An Empirical Examination.” Journal of Real Estate Finance and Economics, 10 (3): 261 – 270.

Doss, Cheryl R. and Steven J. Taff. (1996). “The Influence of Wetland Type and Wetland Proximity on Residential Property Values.” Journal of Agricultural and Resource Economics, 21 (1): 120 – 129.

Earnhart, Dietrich H. (2001). “Combining Revealed and Stated Preference Methods to Value Environmental Amenities at Residential Locations.” Land Economics, 77 (1): 12 – 29.

Environmental Protection Agency. (2001). Our Built and Natural Environments. Washington D.C.

Espey, Molly and Kwame Owusu-Edusei. (2001). “Neighborhood Parks and Residential Property Values in Greenville, South Carolina.” Journal of Agricultural and Applied Economics, 33 (3): 487 – 492.

Freeman, A. Myrick III. (2003). The Measurement of Environmental and Resource Values: Theory and Methods, Second Edition. Resources for the Future Press, Washington, DC.

Garrod, Guy and Ken Willis. (1992). “The Environmental Economic Impact of Woodland: A Two Stage Hedonic Price Model of the Amenity Value of Forestry in Britain.” Applied Economics, 24 (7): 715 – 728.

Geoghegan, Jacqueline. (2002). “The Value of Open Spaces in Residential Land Use.” Land Use Policy, 19 (1) 91 – 98.

Geoghegan, Jacqueline, Lori Lynch and Shawn Bucholtz. (2003). “Capitalization of Open Spaces into Housing Values and the Restidential Property Tax Revenue Impacts of Agricultural Easement Programs.” Agricultural and Resource Economic Review, 32 (1):33 – 45.

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: 251 – 264.

Gibbons, Steve and Stephen Machin. (2003). "Valuing English Primary Schools." Journal of Urban Economics, 53 (2): 197 – 219.

Goldberger, Arthur S. (1968). "The Interpretation and Estimation of Cobb-Douglas Functions." Econometrica, 36 (3-4): 464 – 472.

Halvorsen, Robert and Raymond B. Palmquist. (1980). "The Interpretation of Dummy Variables in Semilogarithmic Equations." American Economic Review, 70 (3): 474 – 475.

Heal, Geoffrey (2001). "Bundling Public and Private Goods." Working Paper, Columbia Business School.

Irwin, Elena G. (2002). "The Effects of Open Space on Residential Property Values." Land Economics, 78 (4): 465 – 480.

Irwin, Elena G. and Nancy E. Bockstael. (2001). "The Problem of Identifying Land Use Spillovers: Measuring the Effects of Open Space on Residential Property Values." American Journal of Agricultural Economics, 83 (3): 698 – 704.

Kennedy, Peter E. (1981). "Estimation with Correctly Interpreted Dummy Variables in Semilogarithmic Equations." American Economic Review, 71 (4): 801.

Lee, Chang-Moo and Peter D. Linneman. (1998). "Dynamics of the Greenbelt Amenity Effect on Land Market: The Case of Seoul's Greenbelt." Real Estate Economics, 28 (1): 107 – 129.

Lutzenhiser, Margot and Noelwah R. Netusil (2001). "The Effect of Open Spaces on a Home's Sale Price." Contemporary Economic Policy, 19 (3): 291 – 298.

Mahan, Brent L, Stephen Polasky, and Richard M. Adams. (2000). "Valuing Urban Wetlands: A Property Price Approach." Land Economics, 76 (1): 100 – 113.

McConnell, Virginia D. and Margaret A. Walls. (2005). "The Value of Open Space: Evidence from Studies of Nonmarket Benefits." Resources for the Future Report, Washington, DC, January.

Pack, Howard and Janet Rothenberg Pack. (1978). "Metropolitan Fragmentation and Local Public Expenditures." National Tax Journal, 31 (4): 349 – 362.

Palmquist, Raymond B. (1991). "Hedonic Methods," in Measuring the Demand for Environmental Quality (J. B. Braden and C. D. Kolstad, Eds.). North-Holland, Amsterdam: 77 – 120.

Palmquist, Raymond B. (1992). "Valuing Localized Externalities." Journal of Urban Economics, 31: 59 – 68.

Parsons, George R. (1990). "Hedonic Prices and Public Goods: An Argument for Weighting Locational Attributes in Hedonic Regressions by Lot Size." Journal of Urban Economics, 27 (3): 308 – 321.

Perkins, George M. (1977). "The Demand for Local Public Goods: Elasticities of Demand for Own Price, Cross Prices, and Income." National Tax Journal, 30 (4): 411 – 422.

Riddel, Mary. (2001). "A Dynamic Approach to Estimating Hedonic Prices for Environmental Goods: An Application to Open Space Purchase." Land Economics, 77 (4): 494 – 512.

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

Santerre, Rexford E. (1985). "Spatial Differences in the Demands for Local Public Goods." Land Economics, 61 (2): 119 – 128.

Schultz, Steven D. and David A. King. (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.

Sheppard, Stephen C. (1999). "Hedonic Analysis of Housing Markets," in Paul C. Cheshire and Edwin S. Mills, eds., Handbook of Regional and Urban Economics, Volume 3, Amsterdam: North Holland.

Smith, V. Kerry, Christine Poulos, and Hyun Kim. (2002). "Treating Open Space as an Urban Amenity." Resource and Energy Economics, 24: 107 – 129.

Tyrväinen, Liisa and Antti Miettinen. (2000). "Property Prices and Urban Forest Amenities." Journal of Environmental Economics and Management, 39: 205 – 223.

Weicher, John C. and Robert H. Zerbst. (1973). "The Externalities of Neighborhood Parks: An Empirical Investigation." Land Economics, 49: 99 – 105.

Table 1: Variable Names and Definitions

Variable name	Definition	Location in equation (2)
Dependent variable		
SALESPRICE	Home sales price ($1997)	$\ln P_{hi}$
Home structure		
LOTSIZE	Lot size (acres)	$\ln X_{hi}$, Z_{hi}
SQUAREFEET	Finished square feet	$\ln X_{hi}$
BATHROOMS	Number bathrooms	$\ln X_{hi}$
AGE	Age of home	$\ln X_{hi}$
FIREPLACE	Equals 1 if home has fireplace; 0 otherwise	Y_{hi}
MONTH[m]	Equals 1 if sold in month m = 1, .., 12; 0 otherwise	Y_{hi}
Amenity distance		
NPARK_D	Distance to neighborhood park (meters)	$\ln d_{NPARK,hi}$
SPARK_D	Distance to special park (meters)	$\ln d_{SPARK,hi}$
GOLF_D	Distance to golf course (meters)	$\ln d_{GOLF,hi}$
CEMETERY_D	Distance to cemetery (meters)	$\ln d_{CEMETERY,hi}$
LAKE_D	Distance to lake (meters)	$\ln d_{LAKE,hi}$
RIVER_D	Distance to river (meters)	$\ln d_{RIVER,hi}$
Amenity size (covariates)		
NPARK_A	Size of neighborhood park (acres)	$S_{NPARK,hi}$
SPARK_A	Size of special park (acres)	$S_{SPARK,hi}$
GOLF_A	Size of golf course (acres)	$S_{GOLF,hi}$
CEMETERY_A	Size of cemetery (acres)	$S_{CEMETERY,hi}$
LAKE_A	Size of lake (acres)	$S_{LAKE,hi}$
Neighborhood (covariates)		
DENSITY	Persons per square mile	Z_{hi}
CBD	Distance to CBD (meters)	Z_{hi}
INCOME	Median household income ($1990)	Z_{hi}
CRIME	Number of reported serious crimes per 1,000 people	Z_{hi}
UNDER18	Percent of population less than 18 years old	Z_{hi}
OVER65	Percent of population aged 65 years and older	Z_{hi}

Note: Table lists and defines the variables that we use to estimate equation (2). Third column indicates location of each variable in equation (2). Note that lot size appears both linearly as a covariate and in its logged form as a direct determinant of home value.

Table 2: Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
SALESPRICE	142,322.00	98,300.05	1,000.00	4,300,000.00
LOTSIZE	0.33	0.73	0.01	45.00
SQUAREFEET	1,863.13	890.66	99.00	35,000.00
BATHROOMS	2.10	0.90	1.00	9.00
AGE	38.00	28.63	1.00	148.00
FIREPLACE	0.50	0.50	0.00	1.00
NPARK_D	468.67	616.42	1.00	28,932.72
SPARK_D	2,265.40	1,705.78	1.00	15,882.51
GOLF_D	2,036.66	1,215.32	1.00	23,427.33
CEMETERY_D	5,102.96	4,623.22	1.00	24,119.25
LAKE_D	1,313.20	1,209.47	1.00	30,684.93
RIVER_D	5,822.94	4,073.83	35.03	19,342.36
NPARK_A	27.08	43.58	0.06	671.66
SPARK_A	1,025.34	1,871.39	9.02	8,601.17
GOLF_A	134.58	85.24	12.91	575.96
CEMETERY_A	55.32	75.26	2.84	455.27
LAKE_A	154.79	570.03	0.07	5,793.59
DENSITY	4,025.71	3,187.65	18.90	29,104.70
CBD	14,514.22	8,383.18	1,181.49	38,945.76
INCOME	43,132.67	13,992.09	4,999.00	150,001.00
CRIME	39.89	19.98	0.00	220.00
UNDER18	27.08	7.67	0.00	54.74
OVER65	9.30	7.92	0.00	73.47

Note: Table is based on estimation sample of 24,862 home transactions in the Twin Cities during 1997. See table 1 for variable definitions. Summary statistics are given for variables prior to logarithmic transformation or normalization.

Table 3: Estimation Results

Variable	Coefficient	Std. Error	t-statistic	Probability
Ln(LOTSIZE)	0.0979	0.0036	26.8800	0.0000
Ln(SQUAREFEET)	0.4974	0.0055	90.2500	0.0000
Ln(BATHROOMS)	0.0825	0.0045	18.1800	0.0000
Ln(AGE)	-0.1335	0.0019	-70.6900	0.0000
FIREPLACE	0.0454	0.0030	15.1400	0.0000
Ln(NPARK_D)	-0.0035	0.0014	-2.5500	0.0110
Ln(SPARK_D)	-0.0252	0.0035	-7.2600	0.0000
Ln(GOLF_D)	-0.0060	0.0039	-1.5500	0.1220
Ln(CEMETERY_D)	0.0084	0.0076	1.1100	0.2680
Ln(LAKE_D)	-0.0342	0.0039	-8.8600	0.0000
Ln(RIVER_D)	-0.0273	0.0099	-2.7500	0.0060
SIZE_NPARK* Ln (NPARK_D)	0.0004	0.0002	2.1400	0.0330
SIZE_SPARK* Ln (SPARK_D)	-0.0003	0.0002	-1.5400	0.1230
SIZE_GOLF* Ln (GOLF_D)	0.0001	0.0006	0.2200	0.8250
SIZE_CEMETERY* Ln (CEMETERY_D)	-0.0002	0.0003	-0.6200	0.5340
SIZE_LAKE* Ln (LAKE_D)	0.0002	0.0001	1.8300	0.0670
LOTSIZE* Ln(NPARK_D)	-0.0001	0.0004	-0.1400	0.8920
LOTSIZE* Ln(SPARK_D)	-0.0027	0.0008	-3.4200	0.0010
LOTSIZE* Ln(GOLF_D)	-0.0002	0.0008	-0.2400	0.8070
LOTSIZE* Ln(CEMETERY_D)	0.0013	0.0007	2.0500	0.0410
LOTSIZE* Ln(LAKE_D)	-0.0037	0.0007	-5.6900	0.0000
LOTSIZE* Ln(RIVER_D)	0.0040	0.0008	5.0500	0.0000
DENSITY* Ln(NPARK_D)	-0.0060	0.0028	-2.1300	0.0340
DENSITY* Ln(SPARK_D)	-0.0165	0.0062	-2.6500	0.0080
DENSITY* Ln(GOLF_D)	0.0165	0.0068	2.4200	0.0160
DENSITY* Ln(CEMETERY_D)	-0.0064	0.0078	-0.8200	0.4100
DENSITY* Ln(LAKE_D)	-0.0016	0.0073	-0.2100	0.8310
DENSITY* Ln(RIVER_D)	0.0143	0.0165	0.8700	0.3850
CBD* Ln(NPARK_D)	0.0125	0.0034	3.7200	0.0000
CBD* Ln(SPARK_D)	0.0093	0.0078	1.1900	0.2330
CBD* Ln(GOLF_D)	0.0139	0.0057	2.4600	0.0140
CBD* Ln(CEMETERY_D)	-0.0009	0.0134	-0.0700	0.9440
CBD* Ln(LAKE_D)	-0.0471	0.0065	-7.2100	0.0000
CBD* Ln(RIVER_D)	0.0139	0.0148	0.9400	0.3470

Table continued on following page.

Table 3: Estimation Results (continued)

Variable	Coefficient	Std. Error	t-statistic	Probability
INCOME· Ln(NPARK_D)*	-0.0117	0.0052	-2.2700	0.0230
INCOME· Ln(SPARK_D)*	-0.0290	0.0094	-3.0700	0.0020
INCOME· Ln(GOLF_D)*	0.0153	0.0098	1.5600	0.1180
INCOME· Ln(CEMETERY_D)*	0.0211	0.0198	1.0700	0.2850
INCOME· Ln(LAKE_D)*	-0.0350	0.0115	-3.0500	0.0020
INCOME· Ln(RIVER_D)*	-0.1489	0.0375	-3.9700	0.0000
CRIME· Ln(NPARK_D)*	-0.0037	0.0032	-1.1400	0.2550
CRIME· Ln(SPARK_D)*	-0.0177	0.0081	-2.1800	0.0290
CRIME· Ln(GOLF_D)*	-0.0034	0.0067	-0.5100	0.6080
CRIME· Ln(CEMETERY_D)*	-0.0067	0.0085	-0.7900	0.4280
CRIME· Ln(LAKE_D)*	0.0287	0.0077	3.7100	0.0000
CRIME· Ln(RIVER_D)*	-0.0054	0.0092	-0.5900	0.5540
UNDER18· Ln(NPARK_D)*	-0.0155	0.0069	-2.2500	0.0240
UNDER18· Ln(SPARK_D)*	0.0238	0.0151	1.5700	0.1160
UNDER18· Ln(GOLF_D)*	0.0038	0.0136	0.2800	0.7830
UNDER18· Ln(CEMETERY_D)*	-0.0010	0.0278	-0.0400	0.9710
UNDER18· Ln(LAKE_D)*	0.0872	0.0167	5.2300	0.0000
UNDER18· Ln(RIVER_D)*	0.1817	0.0455	3.9900	0.0000
OVER65· Ln(NPARK_D)*	-0.0016	0.0023	-0.6900	0.4920
OVER65· Ln(SPARK_D)*	0.0030	0.0041	0.7300	0.4650
OVER65· Ln(GOLF_D)*	0.0136	0.0046	2.9700	0.0030
OVER65· Ln(CEMETERY_D)*	0.0063	0.0085	0.7400	0.4620
OVER65· Ln(LAKE_D)*	-0.0173	0.0057	-3.0300	0.0020
OVER65· Ln(RIVER_D)*	0.0124	0.0155	0.8000	0.4250
MONTH DUMMIES				*Significant*
BLOCK GROUP FIXED EFFECTS				*Significant*
Number of observations				24,862
R-squared				0.8781
R-squared within block groups				0.6009

Note: Regression results are based on data for single-family home transactions in the Twin Cities during 1997. Estimation method is OLS implicitly controlling for block group fixed effects. * indicates variable has been transformed according to equation (5). See text for details. See table 1 and table 2 for variable definitions and descriptive statistics, respectively.

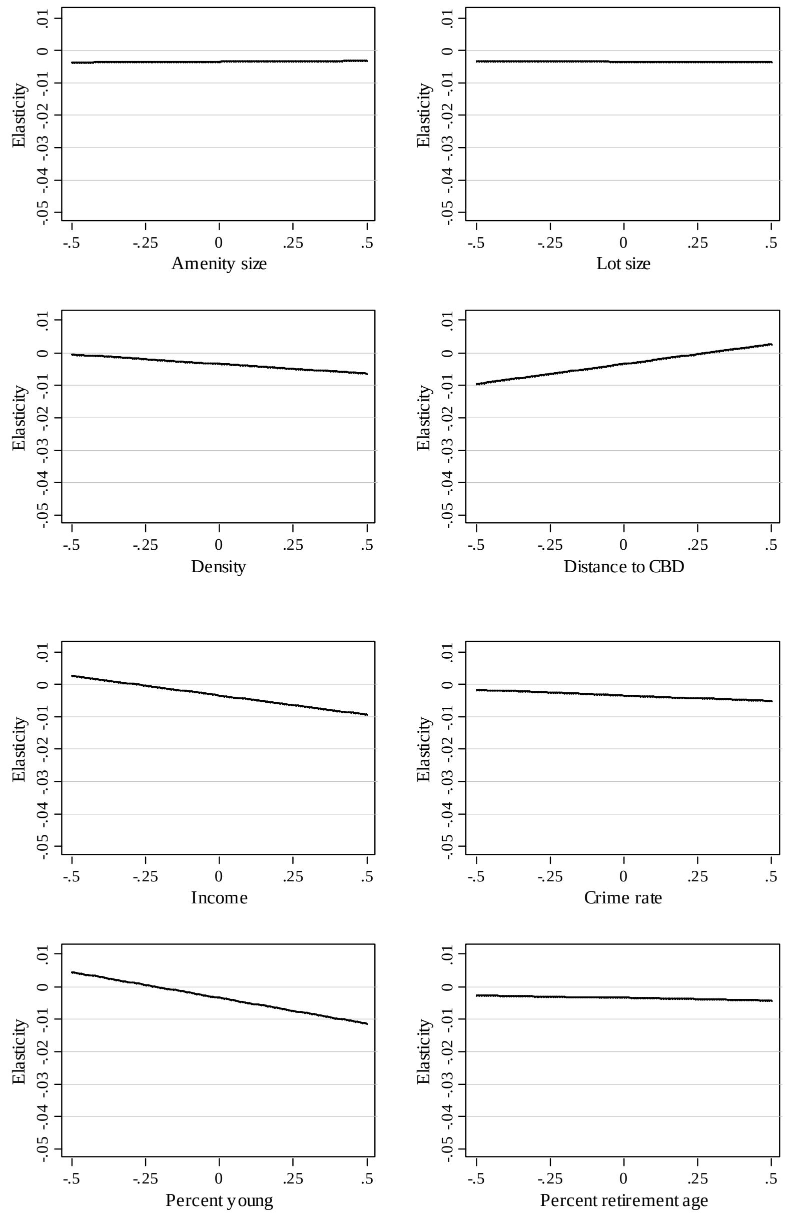


Figure 1: Estimated Relationship Between Elasticity and Covariates: Neighborhood Parks

Note: Figures plot estimated elasticity for neighborhood parks versus each covariate, implicitly holding other covariates constant at their sample mean values. Horizontal axes measure the percent deviation of covariate characteristics from their sample means. Figures are based on coefficient estimates in table 3. Slope effects are statistically significant at or below the 5% level for amenity size, density, distance to the CBD, income, and percent young.

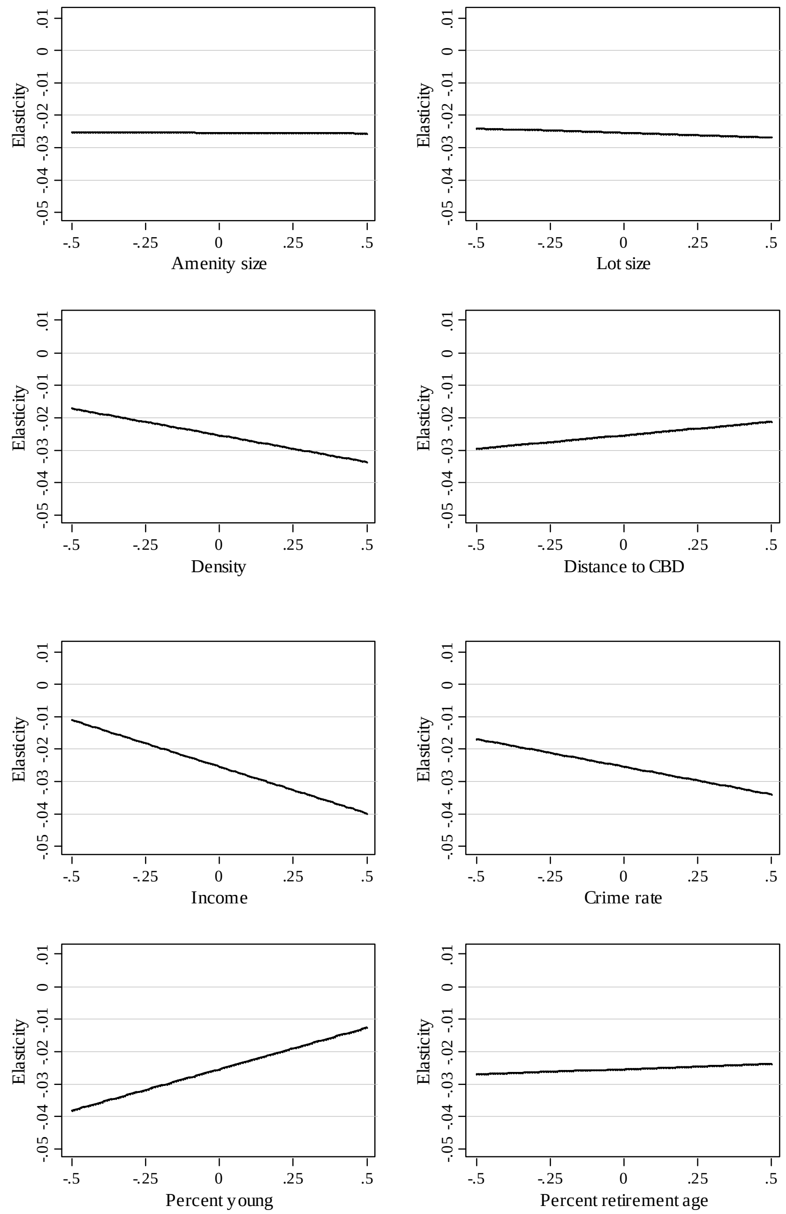
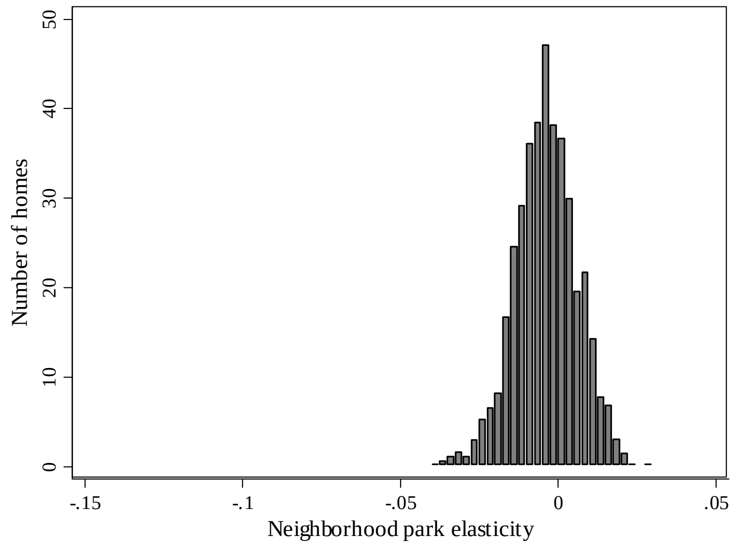


Figure 2: Estimated Relationship Between Elasticity and Covariates: Special Parks

Note: Figures plot estimated elasticity for special parks versus each covariate, implicitly holding other covariates constant at their sample mean values. Horizontal axes measure the percent deviation of covariate characteristics from their sample means. Figures are based on coefficient estimates in table 3. Slope effects are statistically significant at or below the 5% level for lot size, density, income, and crime rate.



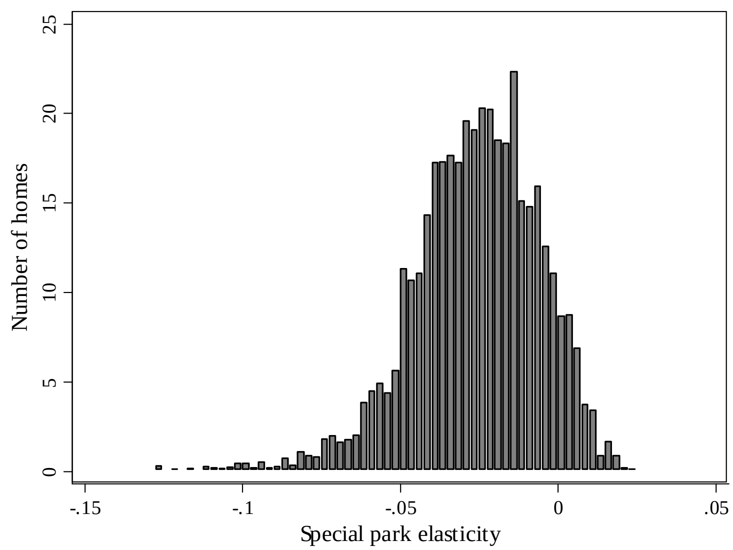


Figure 3: Variation of Elasticity Effects: Neighborhood Parks and Special Parks

Note: Figures show variation of elasticity effects for neighborhood parks and special parks. Histogram for special parks omits 11 observations that have elasticities less than -0.15. The elasticity estimate for neighborhood parks is positive for 36% of homes, ranges from -0.0424 to 0.0311, and has a sample mean of -0.0035 with a standard deviation of 0.0098. The elasticity estimate for special parks is positive for 10% of homes, ranges from -0.4335 to 0.0240, and has a sample mean of -0.0260 with a standard deviation of 0.0212.