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Property values, parks, and crime: A hedonic analysis in Baltimore, MD

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ABSTRACT

While urban parks are generally considered to be a positive amenity, past research suggests that some parks are perceived as a neighborhood liability. Using hedonic analysis of property data in Baltimore, MD, we attempted to determine whether crime rate mediates how parks are valued by the housing market. Transacted price was regressed against park proximity, area-weighted robbery and rape rates for the Census block groups encompassing the parks, and an interaction term, adjusting for a number of other variables. Four models were estimated, including one where selling price was log-transformed but distance to park was not, one where both were log-transformed, a Box–Cox regression, and a spatially adjusted regression. All results indicate that park proximity is positively valued by the housing market where the combined robbery and rape rates for a neighborhood are below a certain threshold rate but negatively valued where above that threshold. Depending on which model is used, this threshold occurs at a crime index value of between 406 and 484 (that is, between 406% and 484% of the national average; the average rate by block group for Baltimore is 475% of the national average). For all models, the further the crime index value is from the threshold value for a particular property, the steeper the relationship is between park proximity and home value.

1. Introduction

This article examines the relationship between property values, proximity to parks, and crime and whether these relationships are interactive. While previous studies have examined the effects of both crime and park proximity individually on home values, there has been no examination of how crime level conditions the relationship between parks and property values. While intuition would suggest that high-crime parks might not be viewed as positive amenities, this has yet to be empirically proven. Further, no information exists as to the level of crime at which a reversal of perception in the amenity value of parks would occur. Such information could yield significant benefits for urban park managers, planners, and law enforcement officials, not only because low crime parks can serve as important amenities, but also because high-crime parks may have the potential to negatively affect their surrounding neighborhoods.

1.1. *Literature review*

Considerable research has attempted to value urban parks, forests, and open space through analysis of property data and stated preferences. The vast majority of these studies use hedonic analysis of property sales data. All of the following studies of property values use this method except one, which is noted. Acharya and Bennett (2001) found that the percentage of open space in the neighborhood of a house varied positively with housing price, all else equal, in an urban watershed in southern Connecticut. They further found that the coefficient on percentage open space was little different whether it was specified for a 1/4 or 1 mile radius around a house. Based on this finding, they concluded that open space is important to homebuyers at various spatial scales, but particularly at the neighborhood scale.

In Quebec City, Des Rosiers et al. (2002) found a vegetation "scarcity effect;" that is, property values increase as the proportion of trees on a property relative to that in the immediate neighborhood (visible from the property) goes up. Further, this effect was more pronounced in neighborhoods with a higher proportion of retired people. Ground cover (lawns, flower beds, etc.) was also found to increase property values for bungalows and cottages. Interestingly, highly dense vegetation in the vicinity of a property was found to reduce its property values.

Morancho (2003) found that housing values decreased with distance to nearest urban green area in Castellon, Spain, although the price effect is described as "humble," and the size of the park had no impact on price. Based on these results, Morancho suggests that having many small green spaces distributed throughout an urban area might be more beneficial than having a few large parks.

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Distinct from the many studies of traditional parks, Nicholls and Crompton (2005) looked specifically at the price effects of urban greenways, or linear areas of open space established along river, stream, or abandoned railroad corridors in Austin, TX. They found that for most areas in their study, adjacency – and likely the access that comes with adjacency – resulted in significant increase in property values. The contention that access is a key factor in this positive valuation was supported by the fact that properties with a view of a greenbelt but without access saw no significant property value increase, a result which also held for properties within 1/2 mile of a greenway. The fact that one of their study sites – a greenway with very rough and steep topography – did not see positive adjacency effects suggest that the usability of the adjacent greenway is critical in determining how it is valued.

Using surveys in addition to hedonic analysis, Peiser and Schwann (1993) found that the presence of green space in subdivisions was positively valued in Dallas, TX, but where public open space is associated with a reduction in private yard space, the private yard space was more highly valued than the public space. However, the study site was somewhat unique in that lots were generally quite large and the so-called "open spaces" were actually strips of land between backyards.

Studying a small city in Finland, Tyrvainen (1997) found that amount of forested area in a "housing district" positively affected property values, proximity to large urban wooded recreation areas increased property value only at the 10% significance level, and, counterintuitively, proximity to small (sub-hectare to a few hectares) forest parks had a negative effect on property values. Proximity to watercourses was also found to increase property values. The author suggests several possible explanations for the negative price effect measured for proximity to small forest parks. One possible explanation relates to the lack of variation in the distance variable, since most properties are within 100 m of such a park. The other is that in such high latitudes, sunlight is scarce, and therefore residents may negatively value nearby trees (which tend to be dense conifers), which have the potential to shade the structure.

Netusil's (2005) results, from Portland, OR, also indicated that open space can be either negatively or positively valued. Looking at how environmental zoning and amenities influenced property values, Netusil found that "urban parks" (where more than 50% of the park is manicured or landscaped, including facilities such as ballfields) are valued negatively between 200 ft and 1/2 mile of a property. The so-called "natural parks", where more than 50% is preserved in "natural" vegetation, had no effect on property values except when located between 1/4 and 1/2 miles from a property, in which case their effect was negative. Trails, roughly corresponding to linear parks or rights of way, had a negative effect on property values when between 0 and 1/4 miles of a property, but that effect became positive between 1/4 and 1/2 miles. The author suggests that this last result may reflect perceptions that being within walking distance of a trail is good, but being too near it might entail noise and other externalities.

Some studies have examined the difference between protected and unprotected open space. Geoghegan (2002) studied Howard County, MD, finding that preserved open space, including private land in conservation easements, positively influenced property values three times more than unprotected open space. Using a spatially adjusted hedonic analysis, Irwin (2002) examined the amount of preserved and developable open space within 400 m of suburban properties in central Maryland and found a similar result, suggesting that it was the lack of development associated with protected open space that increased property values, rather than the specific amenities. Mansfield et al. (2005) looked at suburban homes in North Carolina and found that value increased with proximity to forests and found a greater premium for private forests and a lesser premium for institutional (conserved) forests. Further, they found a negative price effect associated with frontage on institutional forests. The authors suggest that this surprising result may relate to a perception of diminished privacy for adjacent homeowners due to the presence of recreationalists. Increases in an individual lot's tree cover were also found to be associated with an increase in home value. Earnhart (2006) also looked at protected versus unprotected open space, but used contingent valuation combined with conjoint analysis, rather than hedonic analysis. Looking at prairie open space near Lawrence, KS, he found that it was of little value to homeowners when it is unprotected and potentially short-lasting, while preserved open space generated a 5% premium. More specifically, he found that open space is unvalued if the chance of development over the duration of the homeowner's tenure is greater than 50%. The value that residents place on open space was found not to vary with household socio-economic factors.

While neighborhood crime level is often included as a control variable in hedonic analyses of urban green space (e.g., Acharya and Bennett, 2001), the way in which crime level conditions the relationship between green space and property values has not been well studied. Nevertheless, a number of studies have looked at the relationship between parks and crime independent of property values. Several suggest that low and dense vegetation is associated with perceptions of crime risk, because it affords criminals a place to hide. Not only have park police indicated that dense vegetation is regularly used by criminals, but also, in interviews, automobile burglars explain how they use dense vegetation to shield many of their activities, including target selection, examination of stolen goods, and disposal of unwanted goods (Michael et al., 2001).

A considerable body of research has found that urban vegetation is actually related to reductions in crime. In a study of 98 apartment buildings in Chicago, Kuo and Sullivan (2001) found that the greener the immediate surroundings of a building, the lower the crime rate, although that predictor only explained about 8% of the variance. They point out that, in particular, those buildings surrounded by open grassy areas and canopy trees had the lowest crime rates, suggesting that vegetation is likely to increase crime only when it affords opportunities for concealment, particularly where there is undergrowth. In a subsequent publication, Kuo (2003) goes on to explain why well-designed green space might actually decrease crime, suggesting that heavily paved areas with no vegetation are often seen as "no-man's lands" which, by discouraging residential interaction, reduce pedestrian presence and increase crime by making criminals feel safer. When these are greened, people other than criminals spend more time in them, discouraging criminals. This is consistent with Jane Jacobs' contention that places with more "eyes on the street" have more checks on dangerous behavior (Jacobs, 1961).

Criminals can be further discouraged when there is well-maintained vegetation in a neighborhood because it can be seen as a "territorial marker," signifying to criminals that the residents actively care about and are involved with their surroundings (Brown and Bentley, 1993). In such a case, a criminal would presumably move on to a neighborhood where cues suggest there is weaker social organization and neighborhood involvement.

This result is consistent with an earlier work in which Kuo et al. (1998) found that residents disliked and avoided barren common spaces, as many small inner city pocket parks could be described, but that they liked photo-simulations of the same spaces showing the addition of grass and trees. It is also consistent with the finding that the amount of time residents spend in a common space can be predicted by the presence, location, and number of trees (Coley et al., 1997). The same study also found that the closer trees were to residential buildings, the more people spent time outside near them. This suggests that neighborhoods with more trees give rise to stronger social ties, which may yield lower crime levels (Kuo et al., 1998).

Design of parks, then, is clearly an extremely important consideration. Forsyth et al. (2005) dedicate an entire chapter of their book, *Designing Small Parks*, to the goal of discouraging crime and increasing safety. In it, they emphasize the need to eliminate vegetation that can offer concealment and they suggest that people feel safer when parks are more open and the understory is clear. They also cite an important point that is absent in much of the literature; namely many people may be intimidated by parks which are dominated by unruly teens "hanging out" or illegal activities, such as drug dealing. Marcus and Francis (1998) suggest that as overall background activity increases in a park relative to the threatening activity, people feel less intimidated. Hence, any design guidelines that bring more activity into the park will result in a more comfortable atmosphere. Forsyth and Musacchio give several guidelines for safe park design, such as good lighting, good view corridors, and minimal shrub density near circulation routes. They do, however, recognize that many of these guidelines may be inconsistent with conservation-oriented guidelines and that compromises may be needed depending on the purpose of the park.

A few studies have directly examined the relationship between crime and property values and found that neighborhood crime levels negatively affect housing prices, holding other factors constant. Among these are a study by Dubin and Goodman (1982) who found this result in Baltimore, MD in the late seventies. Another study by Bowes and Ihlanfeldt (2001) suggests that transit stations may negatively affect nearby housing values in some cases due to fears of criminal activity, but this effect depends on income and distance to the city center of the neighborhood.

1.2. Research questions

No research has investigated how crime levels condition the way housing values relate to urban parks. This research analyzes property sales transactions in Baltimore, MD, to determine whether the effect of park proximity on home values is conditional upon neighborhood crime level. We propose that not all parks have equal amenity value, some may be negatively valued, and crime is one of the most likely factors explaining this variability. We hypothesize that park proximity is valued negatively in high crime neighborhoods and positively in low crime neighborhoods.

2. Analytical approach and data

2.1. Analytical approach

This study uses hedonic analysis to assess the effects of park proximity and crime levels on property values, holding all else constant. Hedonic analysis, developed by economists such as Quigley and Kain (1970) and Rosen (1974), disaggregates an observed price into a set of unobserved marginal implicit prices. The partial derivative of the price function with respect to the attribute in question can be interpreted as the market-clearing marginal price for that attribute under equilibrium. In the case of real estate, it is frequently used to value attributes that are associated with the sales price of a home, such as views or proximity to protected land. First step hedonic analysis works by regressing sales price against a series of quantifiable attributes, including characteristics about the structure, neighborhood, location and, where relevant, jurisdiction. While many hedonic equations only look at the contributions of individual variables to price without accounting for the interaction among them, other models include terms to account for interactive effects. Some more systematic approaches have been developed to help analyze the need for interactive effects, such as the Casetti expansion method (Casetti, 1972, 1997), which has been used in the hedonic context (e.g. Kestens et al., 2006) and whose purpose is to isolate parameter values displaying "spatial drift," or variability depending on context, then generating interactive terms to account for this variability. While this method was not used in this paper, it underscores the potential importance of interactive terms in hedonic models, which were used here.

We regressed sales price against distance to nearest park, combined robbery and rape rate for the neighborhood surrounding the park, and an interaction term between the two, in addition to a large number of control variables. A list and description of control and main effects variables are given in Table 1. In hedonic analysis, the response variable is very commonly log-transformed due to the presumed non-linear relation between price and attributes. Although some economists believe that proper segmentation of submarkets can yield approximate linearities of implicit price functions across the range of data for each submarket (Dale-Johnson, 1980), it is commonly accepted that such linearities are generally not the rule because consumers are not able to freely untie and repackage bundles of attributes (Freeman, 1979; Rosen, 1974). We chose to compare this semi-log model to a model using a Box–Cox transformation. This approach, first described by Box and Cox (1964) with later elaborations by Halverson and Pollakowski (1979), Spitzer (1982) and Bender et al. (1980), among others, is essentially a power transformation where variables in a linear function are transformed according to

$$y^{(\lambda)} = \begin{cases} \dfrac{(y^{\lambda}-1)}{\lambda} & \text{for } \lambda \neq 0 \\ \ln y & \text{for } \lambda = 0 \end{cases} \qquad (1)$$

The parameter λ is estimated through maximum likelihood to find the optimal transformation of a variable, in this case the dependent. This should yield the transformation that allows the model to best meet many of the assumptions of linear regression, such as normality and constant variance. Once that parameter is estimated, the dependent variable can be transformed according to (1), although there are three "special cases" where $\lambda = 1$, $\lambda = \tilde{0}$, and $\lambda = -1$, corresponding to linear and natural log and reciprocal models, respectively. For our model, we found the optimal λ to be -0.6, which is between a log and reciprocal transformation. Finally, in the interests of exploring potential confounding from spatial effects, we ran a spatially adjusted regression (model 4) using a simultaneous auto-regression covariance family and a neighbor matrix based on the three nearest neighbors in order to assess the sensitivity of our results to potential confounding due to spatial autocorrelation (Cliff and Ord, 1981).

While Box–Cox transformations can also be made of independent variables, we limited our use of this method to the dependent variable, as is common in many hedonic studies. Independent variables were transformed based on *a priori* knowledge from previous hedonic studies, expectations from economic theory, and the spread of data values for each variable. Transformations were assessed based on improvements to model fit. Most independent variable transformations were logarithmic. We log-transformed those variables whose relationship with price we expected to vary with the level of the variable and whose range was sufficiently large that such variation would be discernable. So, for instance, we log-transformed the included distance variables (distance to park, distance to interstate on-ramps, and distance to park) because for all of these we expected declining marginal price effects with increasing distance. The distance to parks term was included in one model as a log-transformed term (model 1) and in another as a linear term (model 2) for comparison. Both models were compared, although we expected model 1 to be much more realistic, since the marginal price effect of moving closer to a park by one unit is likely to be much less pronounced for locations far away from a park than for locations near a park. We also log-transformed structure square footage, as we expected diminishing marginal returns to increase in that variable. Median household income for each block group was log-transformed because there was an extremely large range of income values for the dataset and, given that range, we expected the marginal contribution of neighborhood income level to housing prices would also be non-constant. The only right-side transformation that was not logarithmic was the quadratic term used for housing age. This was based on the expectation that home value would display a "U"-shaped relationship with price due to the competing effects of depreciation and increasing historical value. All of the independent variable transformations included in the models served to significantly increase model R-squared while no other transformation we explored served to do the same. We were aware of the fact that right-side transformations could affect the optimal Box–Cox transformation parameter. However, we found there was virtually no difference in the optimal transformation parameter for a model without transformed independent variables versus the model with the right-side transformations we used.

Eq. (1) below describes model 1, with the distance to park term log-transformed. An interactive term was included between estimated park crime level and the distance to park variable.

$$\ln(P) = \alpha + \beta_{\mathrm{C}}\mathbf{X}_{\mathrm{C}} + \beta_{\mathrm{LC}}\ln(\mathbf{X}_{\mathrm{LC}}) + \beta_{\mathrm{DP}}\ln(X_{\mathrm{DP}}) + \beta_{\mathrm{R}}X_{\mathrm{R}} + \beta_{\mathrm{DPR}}\ln(X_{\mathrm{DP}})X_{\mathrm{R}} + e_i \quad (2)$$

where $\mathbf{X}_{\mathrm{C}}$ is the vector of untransformed control variable, $\mathbf{X}_{\mathrm{LC}}$ is the vector of control variables to be log-transformed, $\ln(X_{\mathrm{DP}})$ is the logged distance to park, X_{R} is the combined robbery and rape rate for park area, $\ln(X_{\mathrm{DP}})X_{\mathrm{R}}$ is the interaction term for previous two, and each β represents a coefficient.

2.2. Data

Property variables came from the Maryland Property View™ database from 2004 (www.mdp.state.md.us/data/index.htm). This dataset included location, sales price, structural variables, renter versus owner occupancy status, and sales dates. Lot area was derived through GIS analysis of parcels (the lot area field from Property View had many omitted values). Neighborhood socio-economic variables, such as income, median age, and percent owner occupancy rate, came from the 2000 US Census, at the block group level. Other control variables coded through GIS analysis included straight line distance to downtown Baltimore and nearest Interstate highway on-ramp. All variables and their descriptions and means/medians are given in Table 1. The criteria for selecting property records included transaction between 1 January 2001 and 1 April 2004, sales price greater than \$60,000 and less than \$1.5 million, single family home or townhome dwelling types, and no omitted values for key variables. This resulted in roughly 15,600 observations.

What constitutes a "park" had to be defined carefully. We used a GIS database of parks and open space for Baltimore City created by the Parks and People Foundation (www.parksandpeople.org). In addition to official city parks (sourced from Baltimore's Department of Recreation and Parks), it also includes all large parcels that are identified as "vacant," owned by the city, and adjacent to a designated city park or a major stream corridor. However, many of the official city parks are extremely small – sometimes under a tenth of a hectare – and without vegetation. For instance, some designated "parks" in the layer included small "playlots," medians between lanes of traffic, highway buffers, landscaping around highway entrances, and small blocks of bare pavement. In order to have a definition of "park" that excluded these types of features, we selected only parks that were both over 2 ha and had at least 50% vegetation cover. Before doing this, artificial boundaries between contiguous parks were dissolved so that each continuous area of park land could be represented with one polygon. Vegetation cover was defined using a 1-m resolution data layer classified from Ikonos imagery in 2003 (Irani and Galvin, 2003). Tree and grass coverage were assigned to park polygons using the Tabulate Areas function in ArcGIS 9.2. Maps of the original parks layer and resulting parks layer are given in Figs. 1 and 2, respectively.

Crime data were obtained from Applied Geographic Solution's (now Tetrad, Inc.) neighborhood crime database (www.tetrad.com/), which gives metrics for different categories of personal, property and violent crime by Census block group. This

Table 1
Regression variables

Control variable names	Description	Mean value	Median value
SALESPRICE	Transacted sales price	\$135,087	\$96,000
SQFTSTRC	Square footage of structure (sq. ft)	1486.9	1288
PARC.AREA	Parcel area (m^2)	383.5	204
BATHS	Full Baths (1) + half baths (0.5)	1.59	1.5
YEAROLD	Structure age as of 2004	75.9	78.0
STRU.MED	Medium structure quality (1/0)	0.283	NA
STRU.HIGH	High structure quality (1/0)	0.004	NA
SFH	Single family home (1/0)	0.304	NA
X2001	Transacted in 2001 (1/0)	0.2497	NA
X2002	Transacted in 2002 (1/0)	0.2698	NA
X2003	Transacted in 2003 (1/0)	0.3947	NA
RENTEROCC	Whether house is renter occupied (1/0)	0.262	NA
MED.HH.INC	Median HH income of BG	\$40,695	\$39,392
P.HS	% HS graduates in BG	0.73	0.75
P.OWNOCC	% owner occupied in BG	0.66	0.67
MED.AGE	Median age of BG	37.0	37
DWNTWN.DIST	D2 downtown (m)	5913	6042
INSTE.DIST	D2 interstate (m)	2064	1892
Main effects names			
D2PARK	Linear distance to nearest park (m)	482	401
ROBB–RAPE05	Combined robbery/rape rate in block groups overlaying park for 2005 (as proportion of national average)	385	382

BG: Census block group.

dataset was available for two time periods, 1999 (based on compiled 1990–1999 data) and 2005 (based on compiled 1999–2005 data). Because the property sales used in the analysis ranged between the two dates (2001–2004), it was not immediately obvious which dataset to use, so results were compared using both. Because the two results were very similar we only present the results based on the 2005 data in the interests of brevity (the interaction term coefficient for model 1 using the 1999 crime data is given in the bottom of Table 2 for comparison). Crime metrics are presented as an index representing percentage of national averages where, for instance, 100 equals the national average and 200 equals twice the national average. Many of Baltimore's neighborhoods are 8–10 times above the national average for crime statistics. In the absence of any guidance in the previous literature for the appropriate crime indicator to use for such a study, we created an indicator that combined robbery and rape rates by taking the average of the two. This was done because we expect that robbery and rape are the indicators most relevant to residents'

Fig. 1. Baltimore parks layer with all polygons included.

perceptions and fears of crime in parks, not only because they are the types of crimes that often occur in parks, but also because they can occur at “random”; that is, they can occur to anyone who happens to be in the wrong place at the wrong time and are less likely to be premeditated than murder or property crime. Among the other available metrics, none seemed as appropriate. Property crime rate was not chosen because it mostly applies to private property. Murder was not chosen because the numbers of these crimes are small, roughly 1/20th of the number of robberies for Baltimore, yet fear of these crimes may be disproportionately large relative to the actual risk due to the press coverage they get, making the correlation between actual rates and perception less reliable. Aggravated assault was not chosen because so many of these incidents include domestic violence and other attacks that occur indoors.

Where a park overlaid only one block group, the crime value of the underlying polygon was assigned to the park. Where a park overlaid multiple block groups, an area-weighted estimate of rob-

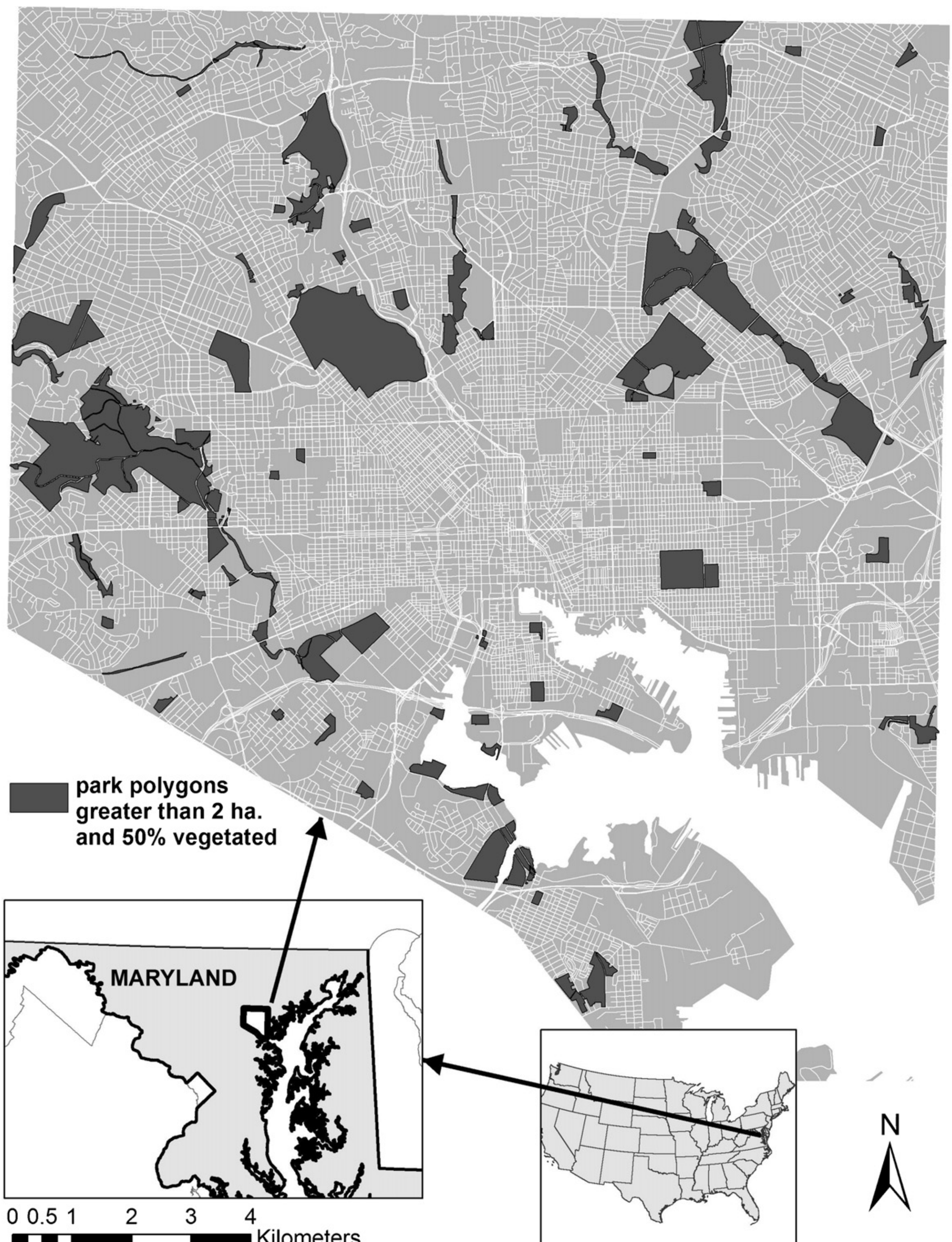

Fig. 2. Baltimore parks layer filtered by selection criteria.

bery and rape rate by park was derived. To do this, robbery rates were plotted by block group and then rasterized. Using the zonal statistics tool in ArcGIS 9.2, the crime rate of the underlying block groups was then averaged and weighted by constituent block group areas for each park.

3. Regression results

The R-squared values for models 1 and 2 are 0.658, indicating a relatively good model fit given the fairly small number of variables. For model 3, the optimal Box–Cox transformation parameter was found to be −0.6. While this transformation did slightly increase the model's adherence to normality and constant variance, it did so at the expense of model fit, dropping R-squared to 0.628. Model 4 did not use an OLS estimator and so did not generate an R-squared value.

For all four models, all variables were significant and all but one was of the expected sign (see Table 2 for models 1 and 2 results, Table 3 for models 3 and 4 results). That exception was percentage of owner occupied structures for the Census block group to which a structure belonged (P.OWNOCC). Its negative value suggests that, after variables like median household income, housing age, and household-level renter-occupancy status are adjusted for, the value of housing is positively associated with the share of rental properties at the neighborhood scale. In other words, it may be that P.OWNOCC is serving as a proxy for some other phenomenon. The phenomenon being proxied may relate to the extensive redevelopment of amenity rich areas such as the Baltimore Inner Harbor, Patterson Park, and Johns Hopkins University districts, where much of the new construction is luxury rental properties. Hence, high renter-occupancy rates may act as a proxy for neighborhood reinvestment once related variables are accounted for.

For the three models where coefficients are comparable (1, 2 and 4), the signs on all variables were the same and all coefficients were of very similar magnitudes. This strong similarity in coefficients between model 4 (the spatial model) and models 1 and 2 is a very good indication that the model is not confounded by spatial autocorrelation and that the results are robust. The coefficients from model 3 (the Box–Cox model) are not directly comparable to those of 1, 2 and 4 without transformation because the dependent variable is on a different scale (however, the relative magnitudes for most coefficient pairs in model 4 are very close to those for the other models, where applying such a ratio is mathematically appropriate). For all models, the quadratic functional form of the housing age variable indicates a U-shaped relationship between house age and price, *cetertis parabis*, with the minimum value occurring at approximately 50 years. In other words, the depreciation associated with housing age brings down housing price until the house reaches a certain age, at which point its increasing historic value begins to marginally compensate for depreciation. This is consistent with recent trends in Baltimore, where historic homes, particularly from the pre-war era, have become sought after and invested in as many historic neighborhoods have gentrified.

Multicollinearity appears not to have been a major problem based on the estimation of variance inflation factors (see Stine, 1995), or VIFs. The general approach is that multicollinearity is not a problem where the VIF of a variable is under 5, and a score of 1 represents perfectly uncorrelated variables. VIFs were estimated for model 1 and are presented in Table 4. Two versions of VIFs were calculated for comparison, one for the model with all terms included and one with the interaction term and squared housing age term removed from the model. This was done because, by definition, the interaction term will be highly autocorrelated with its constituent

Table 2
Regression results for models 1 and 2

ln(SALESPRICE)[a]							
MODEL 1 (log distance to park)				MODEL 2 (linear distance to park)			
Term	Coeff.	*t*-Value	Sig.	Term	Coeff.	*t*-Value	Sig.
Intercept	7.571522	51.19	**	Intercept	7.47178	51.81	**
PARC.AREA	0.000060	8.43	**	PARC.AREA	0.00006	8.45	**
ln(SQFTSTRC)	0.313910	30.32	**	ln(SQFTSTRC)	0.31460	30.27	**
YEAROLD	−0.001502	−4.05	**	YEAROLD	−0.00148	−3.99	**
YEAROLD^2	0.000014	6.19	**	YEAROLD^2	0.00001	6.12	**
BATHS	0.054814	12.88	**	BATHS	0.05496	12.91	**
ln(MED.HH.INC)	0.269202	24.39	**	ln(MED.HH.INC)	0.26830	24.29	**
P.OWNOCC	−0.161452	−8.86	**	P.OWNOCC	−0.16016	−8.80	**
X2001	−0.231016	−23.29	**	X2001	−0.23103	−23.29	**
X2002	−0.146648	−14.98	**	X2002	−0.14650	−14.97	**
X2003	−0.018407	−1.98	*	X2003	−0.01838	−1.98	*
P.HS	0.199222	6.72	**	P.HS	0.20158	6.79	**
MED.AGE	0.009656	17.27	**	MED.AGE	0.00965	17.26	**
RENTEROCC	−0.075508	−12.51	**	RENTEROCC	−0.07556	−12.52	**
ln(DWTWN.DIST)	−0.148374	−18.78	**	ln(DWTWN.DIST)	−0.14853	−18.79	**
ln(INSTE.DIST)	−0.019359	−4.76	**	ln(INSTE.DIST)	−0.01934	−4.75	**
STRU.MED	0.477929	63.50	**	STRU.MED	0.47761	63.26	**
STRU.HIGH	1.137101	27.59	**	STRU.HIGH	1.13620	27.56	**
SFH	0.111187	14.64	**	SFH	0.11180	14.72	**
ln(D2PARK)	−0.021717	−3.20	**	D2PARK	−0.00005	−2.83	**
ROBB–RAPE05[b]	−0.000433	−4.57	**	ROBB–RAPE05[b]	−0.00017	−7.07	**
ln(D2PARK):ROBB–RAPE05[b]	0.000054	3.34	**	D2PARK:ROBB05	0.00000011	2.78	**
R-squared[c]	0.6588				0.6587		
F-statistic[c]	1436.21				1435.78		
Residual S.E.[c]	0.3083				0.3084		

*Significant at the 95% confidence level. **Significant at the 99% confidence level.

[a] Dependent variable.

[b] When the 1999 crime variable (ROBB–RAPE99) was used instead of ROBB–RAPE05 for Model 1, results were almost identical. In model 1, ROBB–RAPE99 had a coefficient of −0.00041(*).

[c] Model-level test statistics cannot be used for comparative purposes between models other than between models 1 and 2.

Table 3
Regression results for models 3 and 4

MODEL 3 (Box–Cox), $(\text{SALESPRICE}^{-0.6}-1)/-0.6$[a]				MODEL 4 (spatial), ln(SALESPRICE)[a]			
Term	Coeff.	*t*-Value	Sig.	Term	Coeff.	*t*-Value	Sig.
Intercept	1.662566652	13087.21	**	Intercept	7.7277141	38.26	**
PARC.AREA	0.000000028	4.60	**	PARC.AREA	0.0000574	8.51	**
ln(SQFTSTRC)	0.000222296	25.00	**	ln(SQFTSTRC)	0.3322934	30.98	**
YEAROLD	−0.000001167	−3.66	**	YEAROLD	−0.0016371	−3.72	**
YEAROLD^2	0.000000013	6.90	**	YEAROLD^2	0.0000113	4.31	**
BATHS	0.000037490	10.25	**	BATHS	0.0439094	11.10	**
ln(MED.HH.INC)	0.000175106	18.47	**	ln(MED.HH.INC)	0.2991833	18.58	**
P.OWNOCC	−0.000125034	−7.99	**	P.OWNOCC	−0.2192359	−8.25	**
X2001	−0.000197827	−23.22	**	X2001	−0.2370199	−27.26	**
X2002	−0.000123903	−14.74	**	X2002	−0.1542016	−17.97	**
X2003	−0.000016346	−2.05	*	X2003	−0.0300874	−3.71	**
P.HS	0.000256986	10.09	**	P.HS	0.2793445	6.42	**
MED.AGE	0.000008160	16.99	**	MED.AGE	0.0097361	11.82	**
RENTEROCC	−0.000066064	−12.74	**	RENTEROCC	−0.0636963	−11.88	**
ln(DWTWN.DIST)	−0.000143406	−21.13	**	ln(DWTWN.DIST)	−0.2059256	−18.40	**
ln(INSTE.DIST)	−0.000012066	−3.45	**	ln(INSTE.DIST)	−0.0207954	−3.28	**
STRU.MED	0.000399448	61.78	**	STRU.MED	0.3663828	45.85	**
STRU.HIGH	0.000597602	16.88	**	STRU.HIGH	0.8721563	21.14	**
SFH	0.000133832	20.51	**	SFH	0.1291038	14.38	**
ln(D2PARK)	−0.000021763	−3.74	**	ln(D2PARK)	−0.0306365	−3.04	**
ROBB–RAPE05	−0.000000453	−5.57	**	ROBB–RAPE05	−0.0005601	−4.00	**
ln(D2PARK):ROBB–RAPE05	0.000000051	3.70	**	ln(D2PARK):ROBB–RAPE05	0.0000758	3.22	**
R-squared[b]	0.628				NA (log likelihood: −55,905)		
F-statistic[b]	1255.13				NA		
Residual S.E.[b]	0.000264				NA		

*Significant at the 95% confidence level. **Significant at the 99% confidence level.
[a] Dependent variable.
[b] Model-level test statistics cannot be used for comparative purposes between models other than between models 1 and 2.

terms and a squared term will be highly correlated with the term it squares (removing interaction terms from VIF calculations is a standard statistical practice). With those terms removed, no variable had a VIF of greater than 3.4, and almost all VIFs were under 2. With the interaction and quadratic terms included, the only variables with VIFs over 5 were those participating in the interaction term and the quadratic housing age terms, as expected, and the D2Park term was only slightly above 5.

Table 4
Variance inflation factors for model 1

Variable	VIF[a]	VIF[b]
PARC.AREA	1.992	1.987
ln(SQFTSTRC)	2.066	2.042
YEAROLD	**14.906**	1.620
YEAROLD^2	**15.066**	
BATHS	1.813	1.805
ln(MED.HH.INC)	2.618	2.598
P.OWNOCC	2.042	2.026
x2001	3.032	3.032
x2002	3.103	3.103
x2003	3.393	3.393
P.HS	2.190	2.190
MED.AGE	1.197	1.196
RENTEROCC	1.162	1.161
ln(DWTWN.DIST)	3.386	3.384
ln(INSTE.DIST)	1.880	1.854
STRU.MED	1.891	1.871
STRU.HIGH	1.138	1.137
SFH	2.009	1.997
ln(D2Park)	**6.598**	1.082
PARK.ROB-RAPE	**44.585**	1.110
ln(D2PARK):ROBB–RAPE05	**50.757**	

Bold values: VIFs for terms participating in either interaction or quadratic terms which, by definition, should be collinear.
[a] For model run with all terms.
[b] For model run excluding interaction term and quadratic term.

Between models 1 and 2, the former, in which distance to park was log-transformed, appears to be more realistic, because common sense suggests that there are diminishing marginal price effects with increasing distance—that is, the price effect of moving one distance unit closer to the park should decrease as distance to the park increases. So, for instance, a move from 50 to 100 m from a park would be expected to have a large impact on price, while a move from 1000 to 1050 m from a park is expected to have only a negligible effect. Nevertheless, the results of both models 1 and 2 are given to illustrate that the overall significance of the interaction term is robust to specification.

In model 1, the logged distance to park variable is negative and significant at the 99% confidence level, indicating that, all else constant, price decreases with increasing distance from a park, but the rate of decrease lessens with increasing distance from the park. As a logged variable in a model with a logged dependent, its coefficient of −0.022 can be interpreted as an elasticity, indicating that for each 1% increase in distance from the park, there is a 2.2% decrease in value. Hence, going from 10 to 20 m from a park has a large impact on price because it represent a large percentage change, while going from 1010 to 1020 m from a park has little impact on price because at that distance from a park a 10-m distance increment represents a small percentage change in distance. The 2005 robbery index variable is also negative and significant at the 99% confidence level, indicating that higher robbery rates for the nearest park result in lower property values. Because it is not logged, its coefficient value of −0.00043 indicates that for each unit increase in the crime score (which ranges from 97 to 885) estimated for a given park, there is a 0.043% decrease in the values of the homes associated with that park (that is, those homes to which that is the closest park). Most importantly, the interaction term between the crime and park distance variables is positive and significant at the 99% confidence level, indicating that for high crime neighborhoods the sign of the relationship between home value and park distance is reversed. Its coefficient of 0.000054 indicates that there is 0.0054% increase in home prices with each 1 unit increase in the product of logged distance and park crime rate.

Results were consistent in model 2, but the linearity of the distance term meant that the effect of park proximity on property values itself did not vary with distance. Its value of −0.00005 indicated that for each additional meter of distance, price goes down by 0.005%, regardless of where that house is on the distance spectrum. Hence, a house that is 1 km away from a park is worth 5% less than an identical house adjacent to a park. The park crime variable is negative and significant at the 99% confidence level. Its coefficient value of −0.00017 indicates that for each unit increase in the crime score estimated for a given park, there is a 0.017% decrease in the values of the homes associated with that park. Finally, the interaction term is positive and significant at the 99% confidence level. Its coefficient value of 0.0000001 indicates that there is a 0.0001% increase in home values for every one unit increase in the product of the term.

It should be noted that regressions were also run in which distance to park was coded as 100, 200 and 300 m dummy variables (separately, for three models). These results, whose detailed results are not presented in this paper, were consistent with model, suggesting that the effect of park proximity levels off with distance, since the coefficient on the dummy variable for the 100-m zone was twice the magnitude of those for the 200 and 300 m zones. All were positive and significant.

The coefficients on the crime, park distance and interaction terms for models 3 and 4 were consistent with those from models 1 and 2. For model 4 (the spatial model), the signs of these three variables were the same and the magnitudes were quite similar (e.g. −0.031 vs. −0.022 for the distance variable and 0.000076 vs. 0.000054 for the interaction variable for models 4 and 1, respectively). In fact, the higher magnitudes for the park distance and interaction term coefficients in the spatial model indicate a slightly more pronounced trend in that model. As for model 3, the coefficients are not directly comparable due to the transformation, but the signs are the same and relative magnitudes are quite similar. For instance, the ratio between the logged distance to park coefficient and the interaction term was −384 for model 1 and −427 for model 3.

Solving the housing price equation shows that the "flipping point," or threshold where the sign of the relationship reverses, occurs at a robbery and rape index of approximately 406 (406% of national average) for model 1, 484 for model 2, 428 for model 3, and 404 for model 4. In other words, for model 1, below a crime level of 406, location close to a park has a positive effect on home values and above that it has a negative effect. The further the crime rate gets above or below that threshold, the steeper the curve is in either direction. These flipping points are all less than the combined rape and robbery index for Baltimore, averaged across block groups, which is 475. The effects of park proximity on home price, holding all else constant, are plotted for model 1 in Figs. 3 and 4, for model 2 in Figs. 5 and 6, and for model 3 for Figs. 7 and 8. In these figures, the y-axis represents property value, which was calculated by solving the hedonic price equation at the mean value of each attribute except crime rate and distance to park. Fig. 3 shows a downward sloping relationship for crime index levels of 100, 200, and 300. Fig. 4 instead shows an upward sloping relationship between home price and distance to park, all else held constant, for crime index levels of 500, 600 and 700. Figs. 5 and 6 give the analogous plots for relationships based on model 2, while Figs. 7 and 9 do so for model 3. Model 4 results are not plotted in the interests of space and because their shapes are quite similar to those in model 1. By comparing the plot results from model 1 and model 3, it can be seen that the Box–Cox transformation yields quite similar results (although the overall magnitude of solved home values is some-

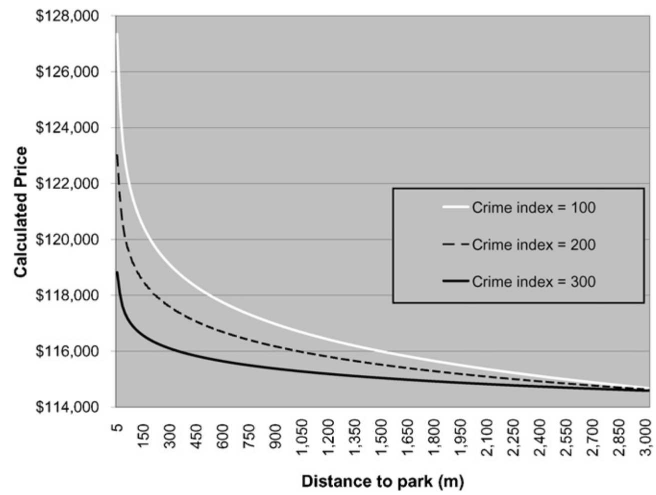

Fig. 3. Relationship between park proximity and home value, holding all else constant, at robbery index values of 100, 200 and 300 for model 1.

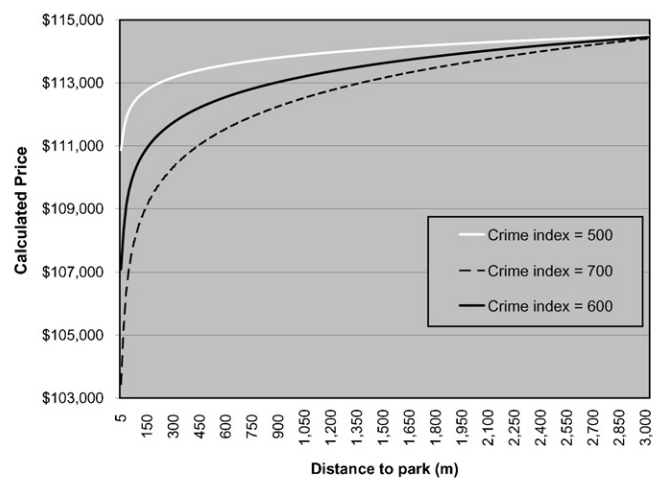

Fig. 4. Relationship between park proximity and home value, holding all else constant, at robbery index values of 500, 600 and 700 for model 1.

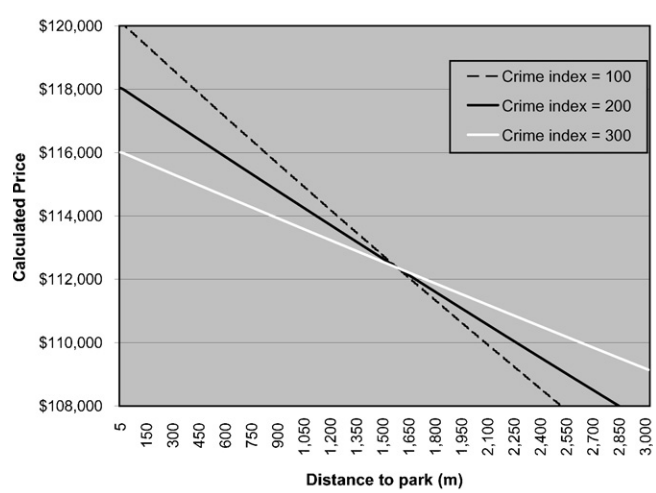

Fig. 5. Relationship between park proximity and home value, holding all else constant, at robbery index values of 100, 200 and 300 for model 2.

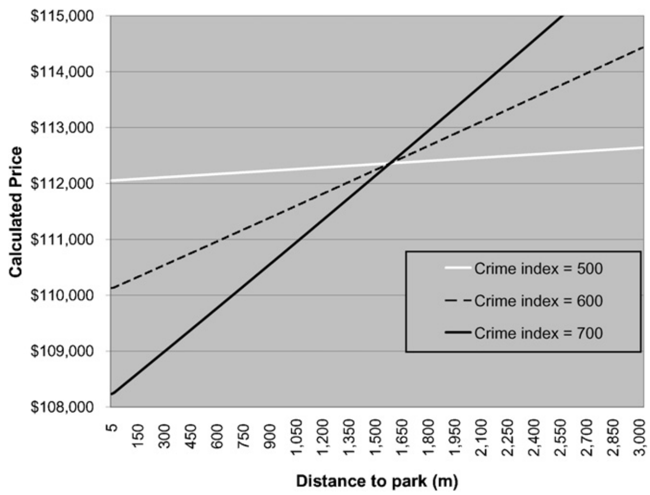

Fig. 6. Relationship between park proximity and home value, holding all else constant, at robbery index values of 500, 600 and 700 for model 2.

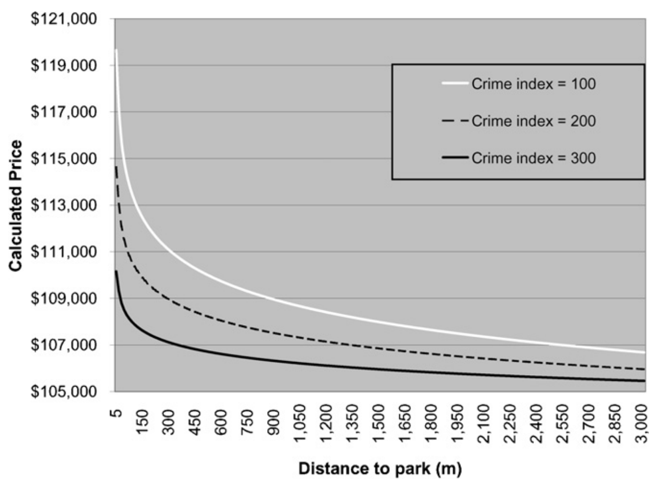

Fig. 7. Relationship between park proximity and home value, holding all else constant, at robbery index values of 100, 200 and 300 for model 3.

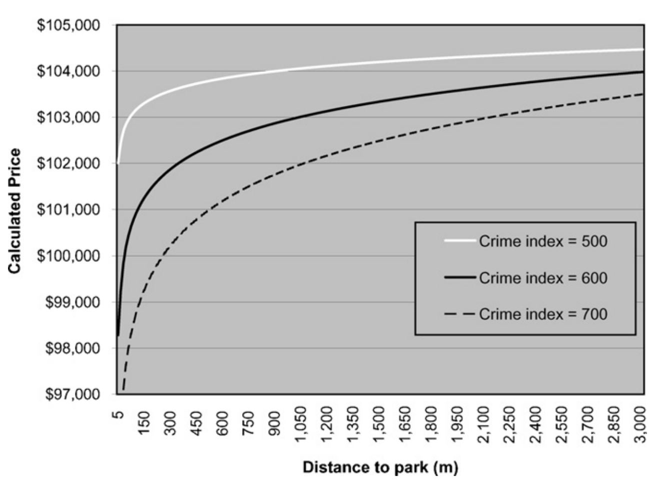

Fig. 8. Relationship between park proximity and home value, holding all else constant, at robbery index values of 500, 600 and 700 for model 3.

what lower for model 3), indicating that the main results are robust to that transformation.

4. Discussion

These results show that crime is a critical factor conditioning how parks are perceived by residents and valued in the Baltimore housing market. When crime rate is relatively low, parks have a positive impact on property values. That threshold value is between 406 and 484% of the national average (which is still lower than the average robbery rate for Baltimore, at 475%). Near the threshold, the value of parks becomes ambiguous. As crime rates climb above this threshold, the direction of the relationship switches and parks negatively influence home values. The steepness of this negative relationship increases as the crime rate increases. Fig. 9 shows parks that are expected to have positive effects (white), negative effects (dark gray), and ambiguous effects (light gray) on property values. What is notable about this figure is the relative dispersion of parks of different crime levels. Rather than being clustered, both low crime and high-crime parks are distributed throughout the city, and often low crime parks will be found very near high-crime parks, without intermediate medium crime parks in between. Also notable is the fact that park crime appears not to be obviously correlated with size or configuration. The largest few parks – Gwynns Falls, Druid Hill, Herring Run and Cylburn Arboretum – run the gamut from low to high crime. Likewise, there are small parks of all crime levels. Linear stream corridor parks also include a range from low (e.g. Moores Run Park) to medium (e.g. Western Run Park), to high (e.g. Chinquapin Run Park) crime, suggesting that riparian amenities do not always yield positive impacts on property.

While Kuo and Sullivan (2001) found that urban vegetation is associated with reduced crime, this study suggests that not all parks are perceived as positive amenities, and that an important factor in differentiating parks is crime. It may be that parks with high crime rates, where park proximity is valued negatively have the less managed and more threatening types of undergrowth vegetation that have been associated with criminal activity (Forsyth et al., 2005; Kuo and Sullivan, 2001; Michael et al., 2001; Nasar et al., 1993). This would make an excellent topic for future study.

The results from this research have several management implications. First, as planners and managers work to rehabilitate existing parks or create new ones, they cannot treat a park as a social island and develop their efforts in isolation. It is important to consider how a park will be affected by and will affect other social dimensions of the neighborhood (Machlis et al., 1997). This suggests that urban natural resource agencies need to work with other government agencies, NGOs, and community organizations to consider how their activities relate to the perception of parks and open spaces. It also suggests that city departments of recreation and parks, police, housing, and community development have common interests and ambitions. For example, after identifying parks located in high-crime neighborhoods, these agencies could work together to develop strategies and implement plans that reduce crime and modify park management, thereby turning an existing neighborhood feature from a liability into an amenity.

Research that addresses how the type, design, and maintenance of vegetation in parks relates to both crime levels and to nearby property prices would be of great use in both facilitating a better understanding of the mechanisms of the relationships described in this paper and in helping to decide where and how to invest in parks. Future research should attempt to address the nature of causality in the relationship between parks, crime and property values. That is, do desirable parks lead to higher property values, do neighborhoods with high demand and hence high property val-

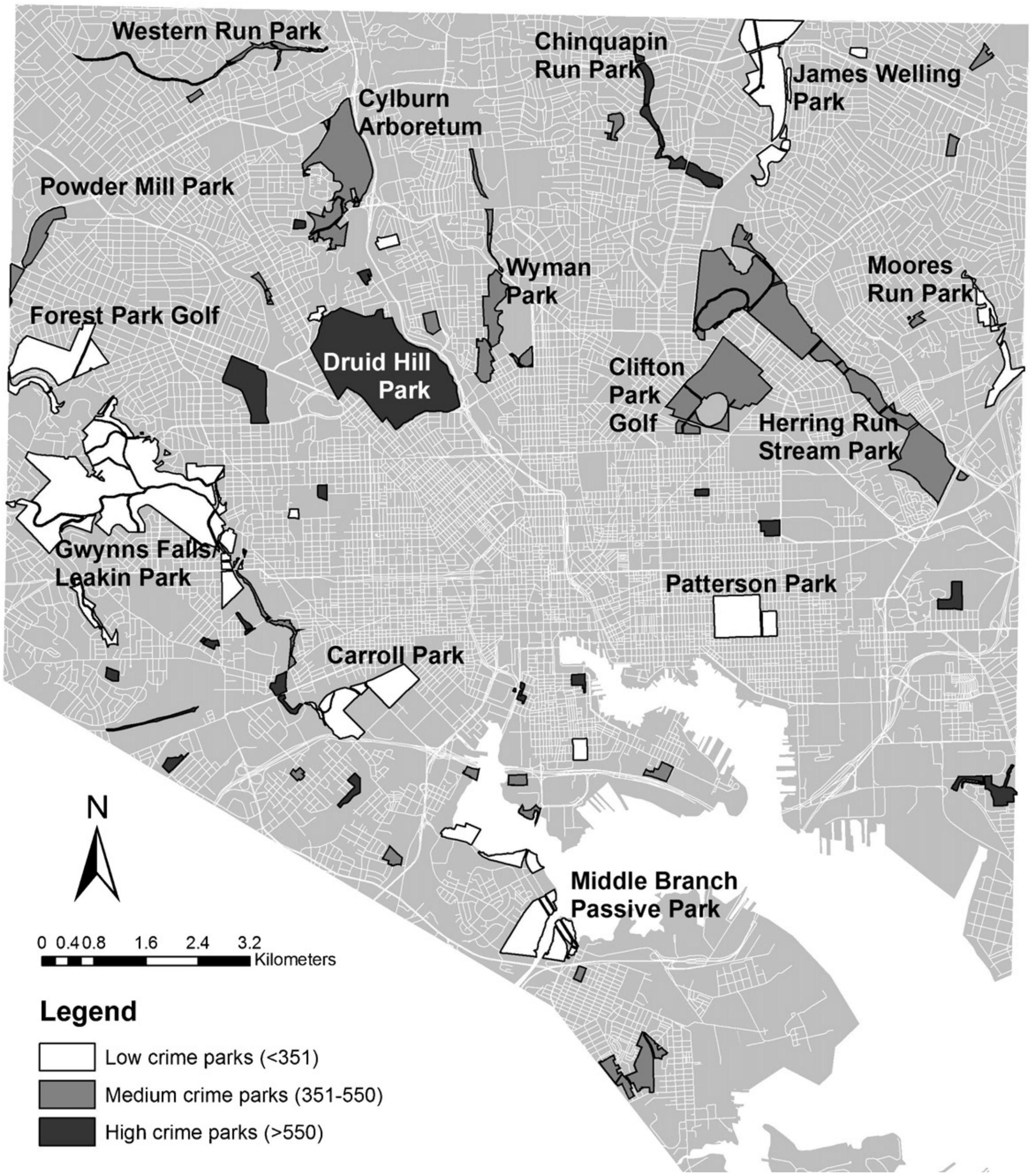

Fig. 9. Map of major Baltimore parks, shaded by crime level of constituent block groups.

ues result in more desirable parks, or do both reinforce each other through some dynamic feedback loop?

There is some anecdotal evidence that in Baltimore, high value neighborhoods tend to invest more (or more successfully lobby for investment) in their nearby parks, thus bringing up park quality. There is also some evidence to suggest that neighborhoods undergoing revitalization and gentrification in Baltimore do invest in their parks. For instance, Patterson Park (Fig. 10) and its surrounding neighborhoods have experienced a significant revitalization over the past 10 years, reflected in higher housing values. This is an area where the park is clearly seen as a vital neighborhood amenity, which is further reinforced by the existence of community-based park management organizations, such as the Friends of Patterson Park (www.pattersonpark.com). This organization sponsors a large number of volunteer management activities in the park, such as trash cleanups, exotic species removal, and tree plantings, as well as recreational activities, such as wine tastings, bird watching, and "fishing rodeos." The Patterson Park example also illustrates how park-based civic institutions can serve as a mechanism to revitalize and "green" the residential streetscapes surrounding parks which, in turn, would be expected to further raise property values. An example of such a spinoff is Project 500 (http://www.pattersonparkneighbors.org/about/showcase.html], a resident-driven project of the Patterson Park Neighborhood Association and Community Development Corporation which seeks to plant new street trees in the neighborhood around the park.

Increased civic engagement from participation in park-based community groups would be expected to yield many positive benefits for a neighborhood. For instance, community involvement in parks serves to boost "eyes on the street" (Jacobs, 1961) both in the park and surrounding neighborhoods, while the landscaping cre-

Fig. 10. High value townhomes fronting on the recently revitalized Patterson Park.

ated through it serves as a "territorial marker" (Brown and Bentley, 1993). Both aspects discourage crime and, in turn, make green spaces even more desirable and lead to further outdoor social interaction. In other words, increased desirability of parks and decreased levels of crime self-reinforce each other, creating a "virtuous green cycle." While there are likely many other factors that help to drive or restrain this cycle, this research shows that the role of parks cannot be discounted in making neighborhoods more desirable.

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References

Acharya, G., Bennett, L.L., 2001. Valuing open space and land-use patterns in urban watersheds. J. Real Estate Finance Econ. 22, 221–237.
Bender, B., Gronberg, T., Hwang, H.S., 1980. Choice of functional form and the demand for air quality. Rev. Econ. Stat. 62, 638–643.
Bowes, D., Ihlanfeldt, K., 2001. Identifying the impacts of rail transit stations on residential property values. J. Urban Econ. 50, 1–25.
Box, G.E.P., Cox, D.R., 1964. An analysis of transformations. J. Roy. Stat. Soc. 26, 211–252.
Brown, B., Bentley, D., 1993. Residential burglars judge risk—the role of territoriality. J. Environ. Psychol. 13, 51–61.
Casetti, E., 1972. Generating models by the expansion method: applications to geographical research. Geogr. Anal., 4.
Casetti, E., 1997. The expansion method, mathematical modeling, and spatial econometrics. Int. Regional Sci. Rev. 20, 9–33.
Cliff, A.D., Ord, J.K., 1981. Spatial Processes: Models & Applications. Pion, London.
Coley, R., Kuo, F., Sullivan, W., 1997. Where does community grow? The social context created by nature in urban public housing. Environ. Behav. 29, 468–494.
Dale-Johnson, D., 1980. Hedonic Prices and Price Indexes in Housing Markets: The Existing Empirical Evidence and Proposed Extensions. Institute of Business and Economic Research, UC Berkeley.
Des Rosiers, F., Theriault, M., Kestens, Y., Villeneuve, P., 2002. Landscaping and house values: an empirical investigation. J. Real Estate Res. 23, 139–161.
Dubin, R., Goodman, A., 1982. Valuation of education and crime neighborhood characteristics through hedonic housing prices. Popul. Environ. 5, 166–181.
Earnhart, D., 2006. Using contingent-pricing space and its duration analysis to value open at residential locations. Land Econ. 82, 17–35.
Forsyth, A., Musacchio, L., Fitzgerald, F., 2005. Designing Small Parks: A Manual Addressing Social and Ecological Concerns. J. Wiley, Hoboken, NJ.
Freeman, A.M., 1979. The hedonic price approach to measuring demand for neighborhood characteristics. In: Segal, D. (Ed.), The Economics of Neighborhood. Academic Press, New York.
Geoghegan, J., 2002. The value of open spaces in residential land use. Land Use Policy 19, 91–98.
Halverson, R., Pollakowski, H., 1979. Choice of functional form for hedonic price equations. J. Urban Econ. 10, 37–49.
Irani, F.W., Galvin, M.F., 2003. Strategic urban forests assessment: Baltimore, Maryland. In: Proceedings from the American Society of Photogrammetry and Remote Sensing 2003 Conference. American Society of Photogrammetry and Remote Sensing.
Irwin, E., 2002. The effects of open space on residential property values. Land Econ. 78, 465–480.
Jacobs, J., 1961. The Death and Life of Great American Cities. Random House, New York.
Kestens, Y., Theriault, M., Des Rosiers, F., 2006. Heterogeneity in hedonic modelling of house prices: looking at buyers' household profiles. J. Geogr. Syst. 8, 61–96.
Kuo, F., Sullivan, W., 2001. Environment and crime in the inner city—does vegetation reduce crime? Environ. Behav. 33, 343–367.
Kuo, F., Sullivan, W., Coley, R., Brunson, L., 1998. Fertile ground for community: inner-city neighborhood common spaces. Am. J. Commun. Psychol. 26, 823–851.
Kuo, F.E., 2003. The role of arboriculture in a healthy social ecology. J. Arboricult. 29, 148–155.
Machlis, G., Force, J., Burch, W., 1997. The human ecosystem. 1. The human ecosystem as an organizing concept in ecosystem management. Soc. Nat. Resour. 10, 347–367.
Mansfield, C., Pattanayak, S., McDow, W., McDonald, R., Halpin, P., 2005. Shades of green: measuring the value of urban forests in the housing market. J. Forest Econ. 11, 177–199.
Marcus, C.C., Francis, C., 1998. People Places: Design Guidelines for Urban Open Space. Van Nostrand Reinhold, New York.
Michael, S., Hull, R., Zahm, D., 2001. Environmental factors influencing auto burglary—a case study. Environ. Behav. 33, 368–388.
Morancho, A., 2003. A hedonic valuation of urban green areas. Landscape Urban Plan. 66, 35–41.

Nasar, J., Fisher, B., Grannis, M., 1993. Proximate physical cues to fear of crime. Landscape Urban Plan. 26, 161–178.
Netusil, N.R., 2005. The effect of environmental zoning and amenities on property values: Portland. Oregon Land Econ. 81, 227–246.
Nicholls, S., Crompton, J., 2005. The impact of greenways on property values: evidence from Austin, Texas. J. Leisure Res. 37, 321–341.
Peiser, R., Schwann, G., 1993. The private value of public open space within subdivisions. J Archit. Plan. Res. 10, 91–104.
Quigley, J.M., Kain, J.F., 1970. Measuring the value of housing quality. J. Am. Stat. Soc. 65, 532–548.
Rosen, S., 1974. Hedonic prices and implicit markets: product differentiation in pure competition. J. Pol. Econ. 82, 34–55.
Spitzer, J.J., 1982. A primer on Box–Cox estimation. Rev. Econ. Stat. 64, 307–313.
Stine, R.A., 1995. Graphical interpretation of variance inflation factors. Am. Stat. 49, 53–56.
Tyrvainen, L., 1997. The amenity value of the urban forest: an application of the hedonic pricing method. Landsc. Urban Plan. 37, 211–222.