ABSTRACT

Title of Thesis:	THE ECONOMIC EFFECT OF COMMUNITY MANAGED OPEN SPACES ON RESIDENTIAL HOUSE SALE PRICES IN THE CITY OF BALTIMORE, MD
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The value of open space is a fundamental issue in landscape architecture. In post-industrial cities, population decline and low land demand have led to a large amount of vacant land. A small percentage of this land is being transformed by community groups into Community Managed Open Spaces (CMOSs). This research paper investigated the effect of parks and CMOSs on residential house sale prices in Baltimore, MD using a hierarchical regression analysis after controlling for property features and neighborhood social, economic and crime information. This study found CMOSs had a positive economic effect on house sale prices, adding 2.7% to properties sold within a quarter mile. These results provide evidence to support CMOSs as an alternative path for communities and planners to manage vacant urban land and the importance of public investment in these types of spaces.

THE ECONOMIC EFFECT OF COMMUNITY MANAGED OPEN SPACES ON RESIDENTIAL HOUSE SALE PRICES IN THE CITY OF BALTIMORE, MD

by

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I wish to thank my sons for their support and patience. Last but not least, I especially want to thank my husband for his unwavering support of my dreams and aspirations.

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List of Abbreviations

ACS	American Community Survey
CAMA	Computer Assisted Mass Appraisal data
CMOSs	Community Managed Open Spaces
MD	Maryland
VIF	Variance Inflation Factor
U.S.	United States

Chapter 1: Introduction

The value of open space is a fundamental issue in landscape architecture. Landscape architects are often challenged by clients and other stakeholders to provide evidence that supports design recommendations for open space. Within the urban context, the value of open space takes on new dimensions, where land use is often driven by strong land demand, limited space and high prices. However, many post-industrial cities have surplus vacant land due to population decline and low demand. A small percentage of this vacant land is being transformed by communities into Community Managed Open Spaces (CMOSs).

The purpose of this study is to investigate the effect of CMOSs on residential house prices in the City of Baltimore, MD. This paper explores the current literature related to the economic value of open space in urban settings, posits the research question, describes the study methodology, summarizes the results and discusses these results in the context of the literature and potential future research.

Section 1. CMOS Defined

CMOSs are vacant land transformed into a range of typologies, such as play lots, pocket parks, community gardens, memorial gardens, art and education spaces and other social spaces (Francis, Cashdan & Paxton, 1984 and Woosley, 2003). These sites are not part of the municipal park system and are maintained by the community (U.S. Forest Service, 2015, p. 11). Woosley (2003) considers CMOSs as neighborhood urban open spaces, and their defining characteristics are that they are physically separate from users homes, require users to make the decision to visit them and are located within the neighborhood.

Photos are very helpful to understand the range of CMOS typologies and their designs. The following pages show photos from three types of CMOSs–a pocket park, a play lot and an ornamental community garden. These before and after photographs reveal site improvements and provide evidence of these sites becoming community amenities. Photos 1 and 2 show Archway Park in the Druid Heights neighborhood of Baltimore, MD. This pocket park, formerly the site of condemned buildings, has become a social place for residents and a gateway to the community.

Photo 1. Archway Park in Druid Heights, Baltimore (Before)

Photo taken by Byoung-Suk Kweon. Used with permission.

Photo 2. Archway Park in Druid Heights, Baltimore (After)

Photo taken by Byoung-Suk Kweon. Used with permission.

Photos 3 and 4 show the Nature Play Space, also in the Druid Heights neighborhood of Baltimore. This nature-based, play-lot provides a safe, natural environment and offers environmental education opportunities for neighborhood children.

Photo 3. Nature Play Space in Druid Heights, Baltimore (Before)

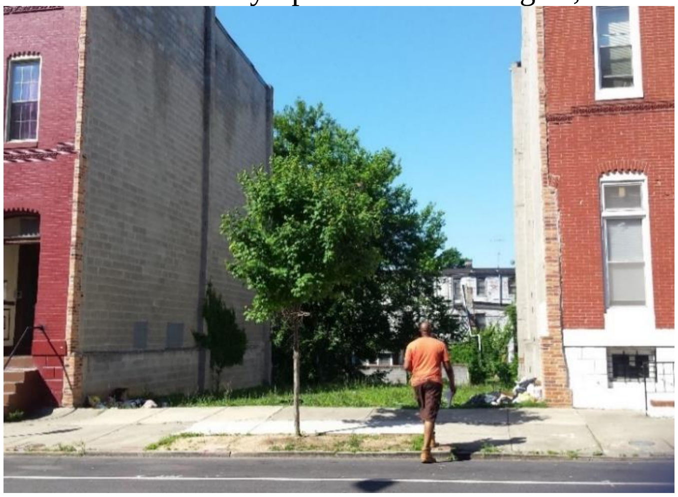


Photo taken by Byoung-Suk Kweon. Used with permission.

Photo 4. Nature Play Space in Druid Heights, Baltimore (After)

Photo taken by Byoung-Suk Kweon. Used with permission.

Photos 5 and 6 show the Wire Avenue Pollinator Garden in Silver Spring, MD. This ornamental community garden, formerly a neglected right-of-way, features a conservation landscape, which inspired other neighborhoods to improve their own rights-of-way.

Photo 5. Wire Avenue Pollinator Garden in Silver Spring, MD (Before)

Photo taken by the author.

Photo 6. Wire Avenue Pollinator Garden in Silver Spring, MD (After)

Photo taken by the author.

CMOSs are not a new phenomenon. Large-scale, urban renewal projects in the 1960s coupled with middle-class flight to suburban areas, left neighborhoods and central business districts in a state of decline in many cities across the country at the time. As a result, cities faced severe financial problems and were not able to attend to their public spaces (Carr, Francis, Rivlin, & Stone, 1992). CMOSs filled the gap in municipal services.

The most common and well-known CMOS typology is the community garden. Lawson (2004) found evidence of community garden programs as far back as the 1890s. More recently, community gardens became common in major cities in the late 1970s to address surplus city-owned land. New York City started its Operation Green Thumb Program in 1978 to lease and administer city-owned land for community gardens. According to Mees (2018), Detroit, Michigan started its own program in the 1980s to provide land for the urban poor to raise food. Baltimore has many community gardens as well as other CMOS typologies, such as memorial spaces, pocket parks, play lots and other recreational, social and educational spaces.

Baltimore has several programs to convert city-owned vacant lots into CMOSs through the Adopt-A-Lot Program (City of Baltimore, Department of Housing and Community Development, 2018) and the Vacants to Value Program (City of Baltimore, Department of Housing and Community Development, n.d). The City has also created a path to permanent land preservation, which is outlined in its guide *Preserving Community-Managed Open Spaces: Criteria and Process* (City of Baltimore, Department of Planning, Office of Sustainability's, 2010).

Many academic studies have investigated how CMOSs provide social, environmental, health and well-being benefits (Dennis & James, 2016; Krones, 2016; Nemeth & Langhorst, 2014; Saldivar-Tanaka & Krasny, 2004; Stone, 2009; and Teig, Amulya, Bardwell, Buchenau, Marshall, & Litt, 2009, and United States (U.S.) Forest Service, 2015). However, the literature is comparatively thin on the economic benefits of CMOSs. The City of Baltimore, Department of Planning (2010) in its guide cites the Voicu and Been study (2008) as their economic justification for supporting these spaces. However, this study only focuses on the community garden typology and sheds little light on the economic benefits of the other CMOS typologies found throughout Baltimore. If CMOSs have a positive effect on house prices, this small-scale intervention can be an avenue through which planners and communities can address vacant lots and bring additional economic benefits to houseowners and other residents.

This study investigated the effect of parks and CMOSs on residential house prices in Baltimore by exploring the current literature, proposing the study's research question, describing its methodology, summarizing the results, an discussing the results in the context of the literature and future research.

Section 2. Literature Review

The current literature on the economic impact of CMOSs has focused on the community garden typology. Voicu and Been's (2008) work in New York City is the most significant study. It showed an average per-garden increase of between 7.5% to 1.9% increase in house sale prices within a 1,000 foot ring (0.2 mi) distance from a garden. The greatest increase of 7.5% was shown adjacent to the community garden and the percentage decreases to 1.9% at 1,000 feet.

Since CMOSs are comparatively less studied, this paper also considers the literature on the economic effect of parks and open space on house sale prices. This literature suggests that parks have an impact and this ranges from a positive sale price premium of 20% to a negative impact under certain conditions.

For example, Crompton (2004) showed a 20% sale price increase on properties abutting passive use parks (i.e., those with trails and other unprogrammed areas) using a hedonic model. He described the capitalization of park land into increased property values as the proximate principle, which is regularly cited in the park valuation literature. Espey and Owusu-Edusei (2001) looked at both small and medium-sized parks in Greenville, South Carolina. Small parks had a 7% sale price premium on houses from 500 to 1,500 feet (0.09 to 0.28 miles). Medium-sized parks had a 6% premium on properties from 200 to 1,500 feet (0.04 to 0.28 miles). They also found that parks created positive sale price premiums regardless of passive or active park programming. However, the relationship between property prices and park proximity can be affected by crime. Troy and Grove (2008) confirmed a positive relationship between park proximity and sale prices in Baltimore, MD. But, once crime exceeded a certain threshold, park proximity had a negative effect on sale prices.

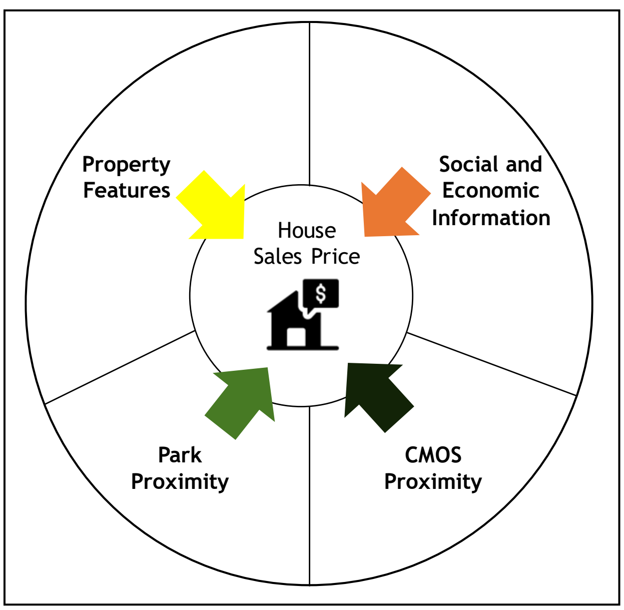
Looking into the research on open greenspace, Conway, Li, Wolch, Kahle & Jerrett (2010) looked at the impact of green cover on house prices in inner city Los

Angeles, CA. Greenspace was defined broadly in this study and included cemeteries, sports fields, lawns, parkways, landscaped area and tree canopy. This study found houses within 200-300 feet (0.04-0.06 mi) of greenspace cover had a 0.076% sale price premium with each 1% increase in greenspace.

<u>Section 3. Research Question</u>

This research paper investigated the effect of parks and CMOSs on residential house prices in Baltimore City using a hierarchical hedonic regression model framework after controlling for property features and neighborhood social, economic and crime information. The relationship between the sale price and these independent variables is shown in Figure 1. The author hypothesized that residential properties within a quarter mile (0.25 mi) of CMOSs experienced a sale price premium while those properties beyond this distance do not.

Figure 1. Hierarchical Hedonic Regression Model Variables

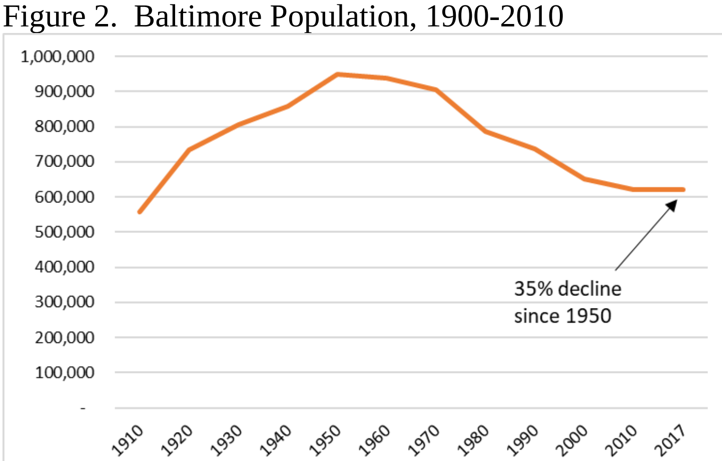


Chapter 2. Methodology

Section 1. Setting

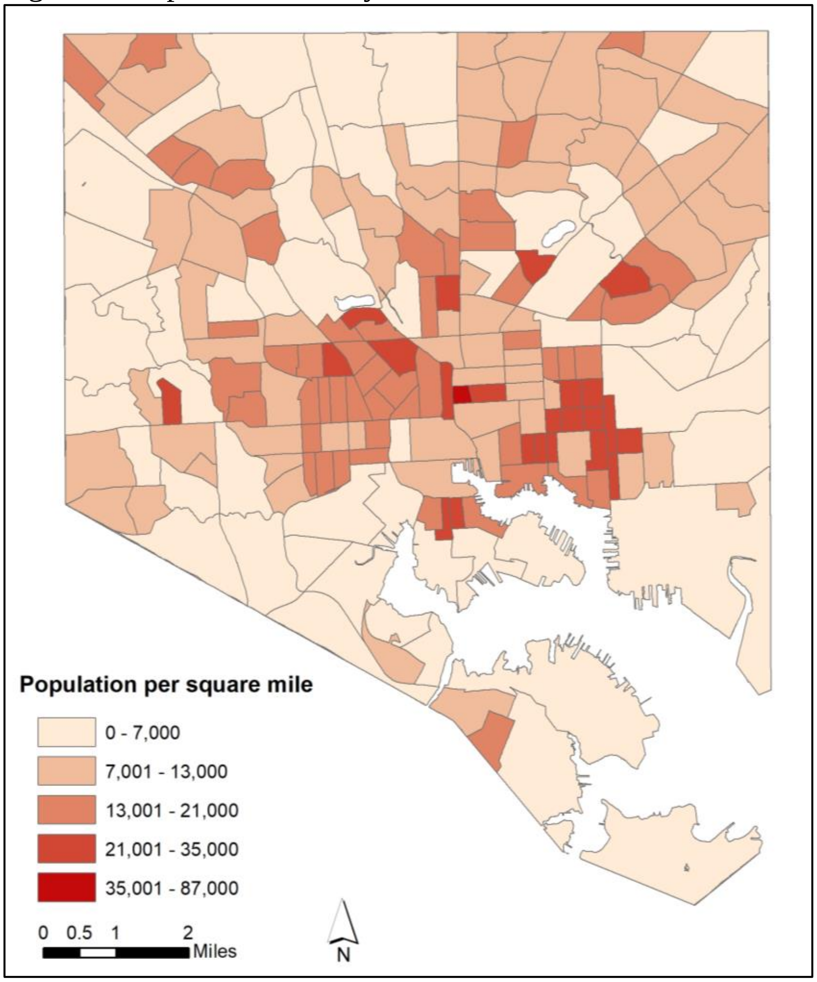
Baltimore is the largest city in the State of Maryland (MD). This ethnically diverse city faces ongoing population decline and a surplus of land as it transitions from heavy industry and the transportation sector to a primarily service-oriented economy (Baltimore Development Corporation, 2016 and City of Baltimore, Department of Planning, 2012). Baltimore's population peaked in 1950 at nearly 950 million residents, and thereafter, the city began to lose residents to the suburbs due to social and economic changes. By 2017, Baltimore's population was 619,796, lower than its population in 1920 and a decline of 35 percent in four decades (American Community Survey (ACS), 2019 and Baltimore Department of Planning, 2020). Figure 2 highlights Baltimore's population trend since 1910. Despite the losses, Baltimore is still a density populated city with between 7,000 to over 87,000 residents per square mile in certain census tracts, shown in Figure 3.

Figure 2. Baltimore Population, 1900-2010



Note. Decennial data from the U.S. Census Bureau (2016) and 2017 data from the ACS, U.S. Census Bureau (2019).

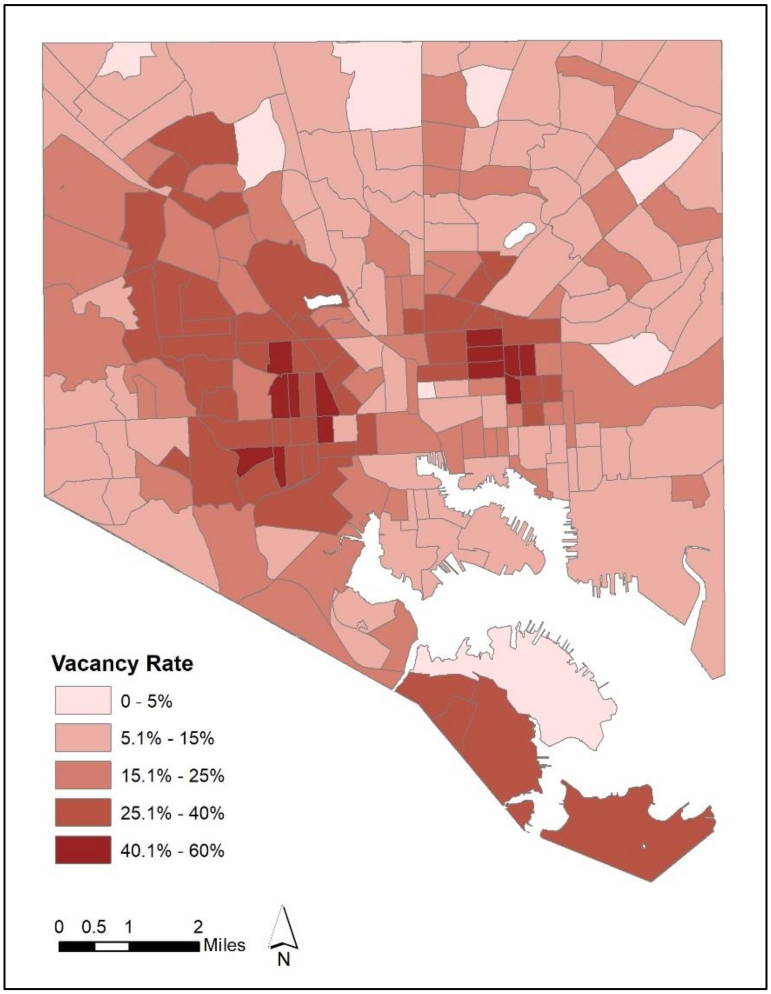
Figure 3. Population Density of Baltimore, MD



Note. Census tract and population data from 2013-2017 ACS, U.S. Census (2019).

The population loss has resulted in a large number of vacant lots and abandoned houses. According to the City of Baltimore, Department of Housing and Community Development (2020), the city has nearly 17,000 vacant buildings and approximately 14,000 vacant lots. Vacancy rates are as high as approximately 60% in certain census tracts with large areas having of the city at least 15% vacancy, as shown in Figure 4.

Figure 4. Baltimore Vacancy Rates by Census Tract



Note. Data from the 2013-2017 ACS, U.S. Census Bureau (2019).

Section 2 Data

This study used information from multiple public data sets. Data preparations and analyses were performed with ArcGIS (ESRI, 2017) and R, statistical analysis software (RCore Team, 2017 and RStudio Team, 2015).

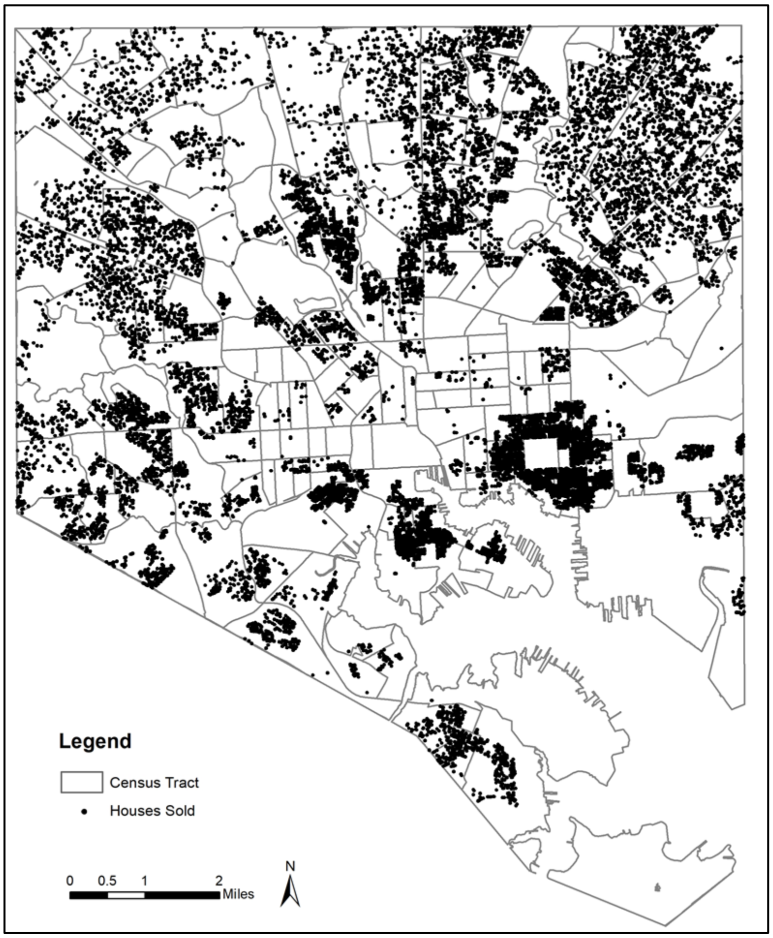
Sale prices and Property Features

Sale prices and property features data from 2016 and 2017 were obtained from the Maryland Department of Planning's (2018) MDProperty View™. These data were available for all real estate transactions in Maryland on a quarterly basis. The data were first selected for transactions in the City of Baltimore and were then filtered to include only arms-length transactions. Non-arms-length transactions (i.e., gifts, foreclosure, and auction) and those records missing transaction type information were excluded. The data were again filtered to retain only single-family properties—detached or attached houses. As shown in Figure 5, residential houses were sold throughout Baltimore during this time period. Other variables used from the sales data include sale price, the square footage of the structure, the year built, the owner occupied property indicator, and the structure grade indicator.

As second data set from MDProperty View™, the Computer Assisted Mass Appraisal (CAMA) data set was also used (Department of Planning, 2018). By matching the records from the sales data with the CAMA data, the following data were added to the record for each house sold: The structural grade indicator, the property grade description, the year built, the square footage of the structure, and the number of full and half bathrooms. Although many of these variables were available in both the sales and CAMA data sets. Unfortunately, bedroom information was not available in the sales, CAMA or another publicly available data and this property feature is therefore not included in this study.

The property parcel size variable was included in the sales and CAMA data but these data were frequently missing. Therefore, parcel data for all properties were matched by the block lot information in the sales data to the parcel data from City of Baltimore (2017) to obtain the parcel polygons. The parcel sizes were then calculated using ArcGIS.

Figure 5. Houses Sold in 2016 and 2017 by Census Tract



Note. MDProperty View™ 2016 and 2017 sales data, Maryland of Planning (2018).

Social and Economic Information

The Baltimore census tract data were obtained from the 2013-2017 ACS (U.S. Census Bureau, 2019). The following indicators for each census tract were used in this study: Total population, census tract area in square miles, the median age of the population, the median household income, families as a percentage of all households, the poverty rate, the percentage of residents having high school diplomas or higher, the unemployment rate, the vacancy rate, and the average years living (tenure) in the census tract. Population density per square mile was derived by dividing the population by the total area in square miles for each census tract.

Crime rates were derived from the City of Baltimore Police Department (2020) Part 1 Victim Based Crime data. The crime rate was assumed to be violent crimes committed with the recent past (2014-2016). The data were extracted for crimes committed within this time period and then filtered to include only violent crimes (rape, robbery, shootings and aggravated assault). After removing duplicates from the results, there were a total of 27,985 crimes during this time period in Baltimore. Using ArcGIS and the recorded X and Y coordinates, the crimes were geolocated and tallied by census tract. These data were then joined with the census tract data and normalized by dividing the number of crimes by the census tract population to arrive at the census tract crime rate.

The percentage of tree canopy cover were derived from the Chesapeake Conservancy (2016) Land Cover Data Project 2013/2014 high resolution satellite data. This one-meter resolution data categorized land cover into twelve classes. Using ArcGIS, these data were reclassified into either tree canopy cover or other classes. Tree canopy cover includes the following: tree canopy, tree canopy over structures, tree canopy over impervious surfaces and tree canopy over impervious roads. Using the Spatial Analyst Zonal Tabulate Area function in ArcGIS, census tract polygons were overlaid onto the reclassified data to calculate the total area of tree canopy cover for each census tract. These data were then converted from square meters to square miles and normalized by dividing the total canopy area by the total census tract area to calculate the percentage of tree canopy cover by census tract. The tree canopy data were then joined to the census tract indicators data, which were subsequently joined with the sales data by matching the tract number of each sale record.

Park and CMOS Proximity Information

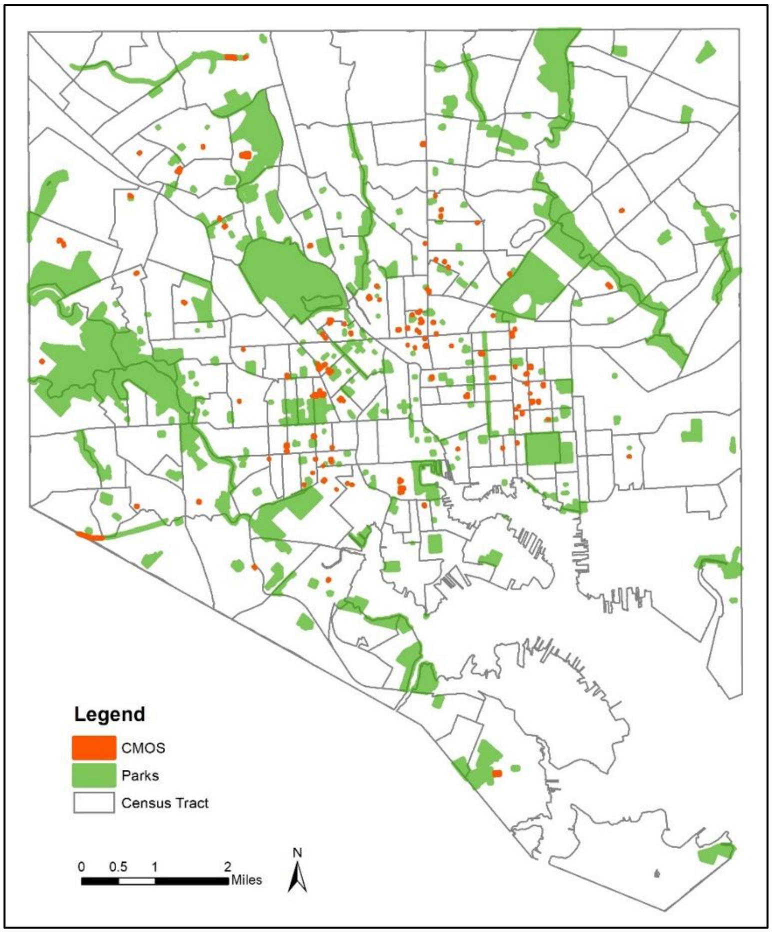
The City of Baltimore Parks data set was obtained by request from the Maryland Department of Planning (2019). Parks in this data set were recorded at the parcel level and was composed of 814 individual parcels. As of 2019, Baltimore has slightly over 4,600 acres of park land. Defining the total area of an individual park was difficult as a park contained one or more parcels with similar or dissimilar names.

The CMOS data was obtained from the Baltimore Neighborhood Indicators Alliance-Jacob France Institute, BNIA-JFI (2014). CMOS data were designated by geolocated centroids, which were manually located by BNIA-JFI staff. To determine the sizes of the CMOSs, the block lot information for each parcel was matched with the block lot numbers in the parcels shapefile to obtain polygons for each CMOS. Typographical mismatches were reviewed and corrected between the data sets. There were several CMOS records with different block lot numbers than the corresponding location in the parcel data. Mismatched CMOS locations were identified by Google Earth satellite imagery (2020) and assigned the corresponding block lot number. Two CMOS locations could not be identified by satellite and were therefore dropped from the analysis. Using the parcel polygons, the total CMOS acreage for each CMOS was calculated using ArcGIS. In total, CMOSs included 504 parcels, covered a total of 34 acres and were located throughout Baltimore.

Similar to the parks data, CMOSs consisted of one or more parcels and could have been recorded under several names. CMOSs with different names were also adjacent to each other at times. Users could perceive these as one CMOS. Given these data constraints, defining the total area of an individual CMOS was as challenging as it was for parks.

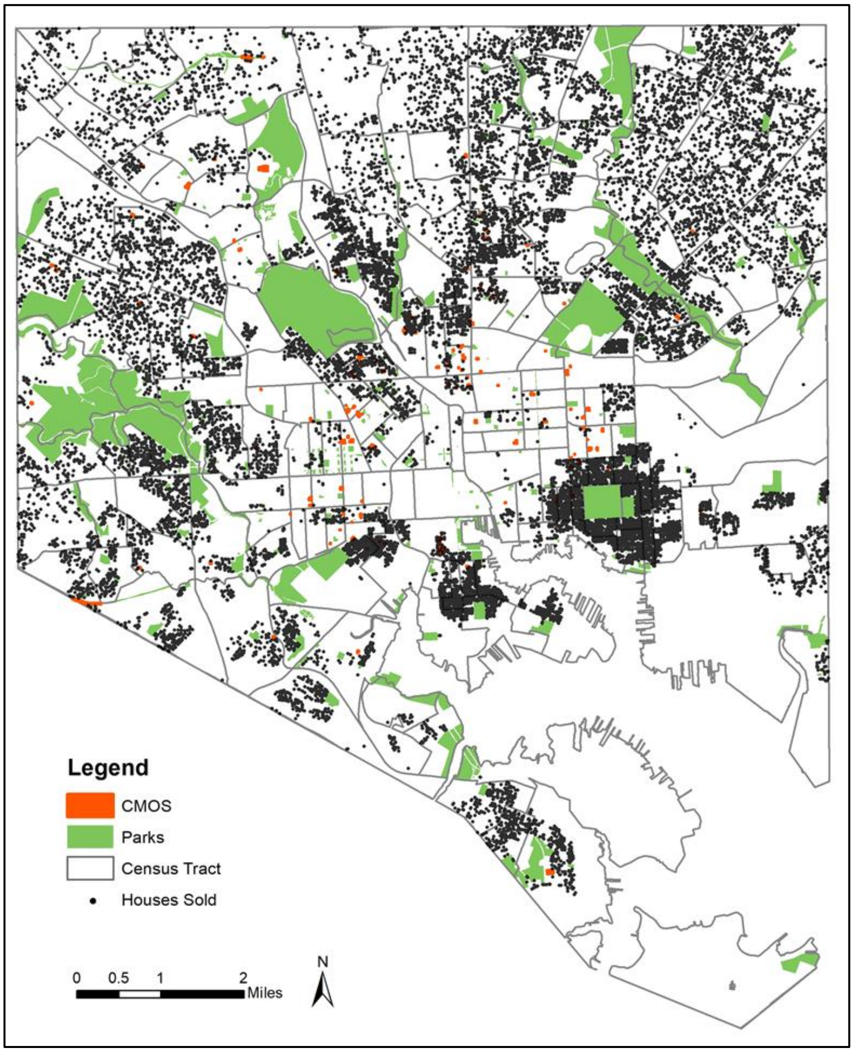
Figure 6 shows the locations of parks and CMOSs. Figure 7 maps the spatial relationship among houses sold, parks and CMOSs. The relationship between sold houses and parks is difficult to discern visually except for one park in the south-east of the city, which has a large concentration of sold houses surrounding it. The relationship between houses sold and CMOSs is even more unclear.

Figure 6. Parks and CMOS Locations



Note. Parks data from the Maryland Department of Planning (2019). CMOS data from Baltimore Neighborhood Indicators Alliance-Jacob France Institute (2014).

Figure 7. Houses Sold, Parks and CMOSs Spatial Relationship



Note. MDProperty View™ from 2016 and 2017 sales data, Maryland Department of Planning (2018). Parks data from Maryland Department of Planning (2019). CMOS data from Baltimore Neighborhood Indicators Alliance-Jacob France Institute (2014).

Data Preparation

Several analysis-based decisions were made to improve the data for use in the model. As noted earlier, the sales and CAMA data sets both contain information for the age, size and condition of the structure. A comparison of the two data sets revealed the CAMA data is older than the sales data, having no records for houses built since 1999. Therefore, the CAMA year built, size and condition of the structure data were dropped and those variables were used from the sales data.

Several dummy variables were also created to improve the model. The owner-occupied indicator, a categorical variable, was converted to a dummy variable. The decision rule was if a property was owner-occupied, it was assigned a 1. All other occupancy categories were assigned a 0.

The house age data were generated by subtracting the year built from 2017 (the last year of this study). According to Do and Grudnitski (1993), the relationship of house age to sale price is negative from 0 to 20 years. After this age, house value beings to increase as a function of the value of the underlying land. Moreover, Clapp and Giaccotto (1998) found age depreciation of houses is nonstationary, which may reflect real estate market demand changes over time. Therefore, a series of dummy variables were created to analyze the data discretely and better describe house value with respect to age. The following groups were used: Less than 10 years old, 11 to 20 years old, 21-30 years old, 31-50 years old, and 51 to 80 years old. If a property age fell within a category range, it was assigned a 1. If its age fell outside of the range, it was assigned a 0. If a property was older than 80 years old, the control variable, it was assigned a 0 for all the age categories.

The bathroom data were combined into a single, total bathrooms variable. The new variable was created by adding the number of full bathrooms and the number of half bathrooms multiplied by 0.5. Although this method loses the detail of half versus full bathrooms, this level of property detail was not required in the model.

To determine the effect of park and CMOS proximity on sale price, the distances from a sold property to the nearest park and to the nearest CMOS data were generated and dummy variables were created. Beginning with the park data, the Euclidian distance in feet from each property sold to the nearest park was calculated using the Near Analysis function in ArcGIS. This process was repeated for the distance from each property to the nearest CMOS.

Next a dummy variable was created to indicate if a property was within the walkable distance to a park. The distances used for this walkability range from 0.0-0.28mi in the literature. Yang and Diex-Roux (2012) noted that 0.25mi (1,320 ft) is frequently used in the literature as the benchmark distance for walkability between two destinations. This study thus used less than 0.25mi as the threshold for determining economic impact. Properties within a quarter mile of a park were assigned a 1 and properties beyond this distance were assigned a 0. A CMOS dummy variable was also created. Similarly, if a property was less than 0.25 mi (1,320 ft) from a CMOS, it was assigned a 1. Properties beyond that distance were assigned a 0.

To prepare the data for the regression model, all variables were checked for non-normal distributions and outliers by visual plot inspection and calculating descriptive statistics. These tests revealed that the sale price, parcel size, and median household income data were non-normally distributed and required transformation. The natural log of each variable was taken and the new variables were named price (logged), parcel size (logged), and median household income (logged), respectively.

The data were then trimmed to remove outliers greater than three standard deviations above and below the mean. Thus, records with price (logged) greater than 14.77 or less than 8.29 were trimmed. Similarly, those with structure square footage greater than 10.18 or less than 8.29 were removed. And, the parcel size (logged) greater than 10.18 and less than 5.14 were trimmed. The total remaining records after trimming were 23,375. Table 1 lists the model variables and summarizes the data preparations.

Table 1. Model Variables and Data Preparations

Variables	Description
Sales price	
Price (logged)	= ln (Price)
Property Features	
Owner occupied property	= Owner occupied property = 1; other occupancy types = 0
Square footage of structure	
Parcel size in feet^2 (logged)	= ln (parcel size in feet^2)
Age	=2017 - year built
Age <10years	= Age < 10 = 1; other age = 0
Age 11_20 years	= Age 11-21 years =1; other age = 0
Age 21_30 years	= Age 21-30 years = 1; other age = 0
Age 31_50 years	= Age 31-50 year = 1; other age = 0
Age 51_80 years	= Age 51-80 = 1; other age = 0
Age > 80 years	= 0 in all age categories
Structural condition rating	= 2 (lowest) to 7 (highest)
Number of bathrooms	= Number of full bathrooms + number of half bathrooms*(0.5)
CT Social and Econonmic information	
CT population	
CT area in square miles	
CT population density	= CT population / CT area (miles^2)
Population median age in years	
Median household income in $ (logged)	= ln (Median household income)
Families as a percentage of all households	
Poverty rate in percent	
Percentage of high school diploma or higher education	
Unemployment rate in percent	
Vacancy rate in percent	
Number of Years living (tenure) in census tract	
Rate of violent crimes	= Sum of (robbery, rape, shooting and aggraved assault for CT)/total CT population
Total acres of canopy by census tract	= Sum of total acres classified as canopy, canopy over structures, canopy over impervious surfaces, and canopy over impervious roads
Percentage of tree canopy	= Total acres of canopy by CT/Total CT acres
Parks and CMOS Proximity Information	
Distance to nearest Park in feet	= Euclidian distance from property to nearest park in feet
<0.25 mile or less distance to park (1/0)	= Park_D < 1,320 feet = 1; Park_D > 1,320 feet = 0
Distance to nearest CMOS in feet	= Euclidian distance from property to nearest CMOS in feet
<0.25 mile or less distance to CMOS (1/0)	= CMOS_D < 1,320 feet = 1; CMOS+B1:E47_D > 1,320 feet = 0

Section 3 Analytical Approach

To measure the impact of CMOSs on residential house prices, this paper used a hierarchical hedonic regression model. In general, hedonic regression models measure the impact that independent variables have on the price or demand for a good. The hierarchical form adds variables with each successive iteration of the model.

This method reveals the contribution of each variable category to the explanation of underlying data variation in the model as indicated by R^2 and the change of R^2 (Kim, 2016). The model used in this study can be described using the following equations:

(1) $\ln P_i = \alpha + \beta H_i + \varepsilon_i$

(2) $\ln P_i = \alpha + \beta H_i + \gamma T_c + \varepsilon_i$

(3) $\ln P_i = \alpha + \beta H_i + \gamma T_c + \delta K_i + \varepsilon_i$

(4) $\ln P_i = \alpha + \beta H_i + \gamma T_c + \delta K_i + \rho C_i + \varepsilon_i$

where $\ln P_i$ is the log of the sale price of property i; H_i is a vector of property features, including the square footage of the structure, parcel size, number of bathrooms, age, structural condition grade, its occupancy use type; T_c is a vector of social and economic information including: Population density, population median age, median household income, family households as a percentage of all households, the poverty rate, the rate of high school diploma attainment or higher, the unemployment rate, the vacancy rate, percentage of owner-occupied properties, years of living (tenure) in the census tract, the crime rate, and percentage of tree canopy cover; K_i is a dummy variable indicating if a property is located within a quarter mile of a park; C_i is a dummy variable indicating if a property is located within a quarter mile of a CMOS.

The coefficients to be estimated are α, β, γ, δ, and ρ, and ε is an error term. Sale prices are measured in logarithms and can be interpreted as approximately the price percentage change resulting from one additional unit of the independent variable, for small values. Or, mathematically, for small values of β, $e^{\beta} \approx 1 + \beta$.

Chapter 3: Results

The results of this study are presented by discussing the descriptive statistics, exploring the relationships among the variables as indicated by their pair-wise correlations, summarizing of the results of the hierarchical hedonic regression model, and reviewing the model's variance inflation factors (VIFs).

The descriptive statistics revealed several interesting characteristics about the data, as seen in Table 2. First, the median sale price was lower than the mean and the standard deviation was nearly has large as the mean. This suggests a wide range of sale prices. Next, the age dummy variable revealed the housing stock in Baltimore is very old and 66% of the houses sold were more than 80 years old. Houses aged 0 to 50 years totaled only 2.4% of the data and were therefore compressed into one dummy variable in the final model.

Interestingly, only 38% of those properties were solely owner-occupied. The data also revealed the population median age in Baltimore was 35.4 years old with a small standard deviation of 5.2 years, suggesting many millennials have made Baltimore their house. Interestingly, the data indicate 73.6% of properties were sold within a quarter mile of a park, whereas, only 25.6% were within a quarter mile of a CMOS.

The correlations between the variable pairs revealed the direction and the strength of the relationship between each pair. These data are displayed as a matrix in Table 3. The relationship between price and median household income was positive and moderately strong at r = 0.52. Median household income also had a strong positive relationship with educational attainment at r = 0.65. The relationship between income and unemployment was negative and fairly strong at r = -0.7163. And, median household income was correlated with the poverty rate at r = -0.75.

Table 2. Descriptive Statistics by Variable Type

Continuous variables	Mean	Median	Standard deviation
Sales price	$154,154	$ 124,000	$ 147,884
Property features			
Square footage of structure	1,362	1,253	456
Parcel size in feet^2	3,108	1,738	3,211
Structural condition rating	2.93	3.00	0.86
Number of bathrooms	1.27	1.00	0.62
Census tract social and economic information			
CT Population density	11,577	10,000	7,638
Population median age in years	36.3	35.4	5.2
Median household income	$ 60,891	$ 53,194	$ 28,460
Families as a percentage of all households	53.0	54.9	11.4
Poverty rate in percent	18.1	16.9	10.1
Percentage of high school degree or higher education	85.4	86.8	8.7
Unemployment rate in percent	8.8	8.2	5.2
Vacancy rate in percent	15.6	13.8	8.2
Number of Years living (tenure) in census tract	19.7	19.0	4.3
Rate of violent crimes	12.9	10.6	7.8
Percentage of tree canopy	24.1	24.0	15.9

Dummy variables	Count	% of total records
Property features		
Owner occupied property indicator (1/0)	8791	38%
Other occupancy type indicator (0/0)	14584	62%
Age 0-10 years (1/0)*	62	0.3%
Age 11-20 years (1/0)*	63	0.3%
Age 21-30 years (1/0)*	171	0.7%
Age 31-50 years (1/0)*	246	1.1%
Age 51-80 years (1/0)	7,414	32%
Age older than 80 years (0/0)	14,877	66%
Park proximity		
<0.25 mile or less distance to park (1/0)	17,209	73.6%
0.25 mile or greater distance to park (0/0)	6,166	26.4%
CMOS proximity		
<0.25 mile or less distance to CMOS (1/0)	5987	25.6%
0.25 mile or greater distance to CMOS (0/0)	17388	74.4%

Note. *Age 0-50 years were combined into a single category in the model due to the low percentages in these categories.

Table 3. Variable Correlation Matrix

	Price	SQFTSTR	Parclsz	BATHS	Age	CTPDnst	PMedAge	MdHHInc	PctFmCT	poverty	HSrHghr	Unemply	vacancy	YrsinCT	CTcrime	PctCnpy	PARK_Ds	CMOS_Ds
Price	1.00																	
SQFTSTR	0.35 ***	1.00																
Parclsz	0.10 ***	0.39 ***	1.00															
BATHS	0.27 ***	0.38 ***	0.31 ***	1.00														
Age	0.20 ***	0.14 ***	-0.23 ***	-0.10 ***	1.00													
CTPDnst	0.08 ***	0.05 ***	-0.32 ***	-0.09 ***	0.22 ***	1.00												
PMedAge	-0.13 ***	0.12 ***	0.40 ***	0.10 ***	-0.26 ***	-0.37 ***	1.00											
MdHHInc	0.52 ***	0.08 ***	-0.02 *	0.11 ***	0.32 ***	0.09 ***	-0.21 ***	1.00										
PctFmCT	-0.31 ***	-0.08 ***	0.27 ***	0.04 ***	-0.42 ***	-0.22 ***	0.16 ***	-0.30 ***	1.00									
poverty	-0.38 ***	-0.01	-0.14 ***	-0.14 ***	-0.07 ***	0.12 ***	-0.02 *	-0.75 ***	0.20 ***	1.00								
HSrHghr	0.39 ***	0.17 ***	0.16 ***	0.15 ***	0.12 ***	0.02 ***	-0.06 ***	0.65 ***	-0.28 ***	-0.68 ***	1.00							
Unemply	-0.44 ***	-0.03 ***	0.04 ***	-0.09 ***	-0.27 ***	-0.07 ***	0.15 ***	-0.72 ***	0.46 ***	0.66 ***	-0.49 ***	1.00						
vacancy	-0.27 ***	0.03 ***	-0.19 ***	-0.17 ***	0.10 ***	0.08 ***	-0.05 ***	-0.46 ***	0.16 ***	0.63 ***	-0.54 ***	0.51 ***	1.00					
YrsinCT	-0.41 ***	0.00	0.14 ***	-0.02 ***	-0.36 ***	-0.16 ***	0.30 ***	-0.58 ***	0.47 ***	0.36 ***	-0.30 ***	0.64 ***	0.28 ***	1.00				
CTcrime	-0.23 ***	-0.08 ***	-0.29 ***	-0.17 ***	0.13 ***	0.14 ***	-0.16 ***	-0.46 ***	-0.07 ***	0.60 ***	-0.60 ***	0.30 ***	0.50 ***	0.05 ***	1.00			
PctCnpy	-0.07 ***	0.19 ***	0.55 ***	0.19 ***	-0.37 ***	-0.48 ***	0.44 ***	-0.12 ***	0.40 ***	-0.12 ***	0.21 ***	0.12 ***	-0.17 ***	0.40 ***	-0.39 ***	1.00		
PARK_Ds	0.01	0.10 ***	0.39 ***	0.16 ***	-0.20 ***	-0.19 ***	0.26 ***	0.02 ***	0.22 ***	-0.10 ***	0.04 ***	-0.02 ***	-0.18 ***	0.00	-0.12 ***	0.21 ***	1.00	
CMOS_Ds	0.00	-0.08 ***	0.33 ***	0.06 ***	-0.34 ***	-0.30 ***	0.19 ***	0.05 ***	0.26 ***	-0.30 ***	0.18 ***	-0.09 ***	-0.31 ***	0.02 ***	-0.33 ***	0.27 ***	0.27 ***	1.00

Notes. Significance levels: * p<.01, ** p<.001, ***p<0

Abbreviations. SQFTSTR: Square footage of structure, Parclsz: Parcel size, BATHS: Number of full and half bathrooms, Age: Age of house, CTDnst: Census tract population density, PMedAge: Population median age, MdHHInc: Median household income, Poverty: Poverty rate, HSrHghr: High school diploma attainment or higher, Unemploy: Unemployment rate, Vacancy: Vacancy rate, YrsinCT: Number of years living in the census tract (tenure), CT crime: Census tract crime rate, PctCnpy: Percentage of tree canopy, Park_Ds: Distance to nearest park, and CMOS_Ds: Distance to nearest CMOS

The hierarchical hedonic regression model estimated the impact of the independent variables on house sale prices and was performed by adding variables with each iteration of the model. R^2 data indicated the model had a relatively good fit to the data. Model 1 revealed that all property features except bathrooms were significant at the $p < 0.0001$ level and it had an R^2 of 0.2387, which was significant at the $p < 0.0001$ level. Model 2 revealed that all the social and economic information were significant at $p < 0.0001$ level with an R^2 of 0.5567, which improved R^2 by 0.3180 over Model 1. Model 3 added the park proximity information and was significant at the $p < 0.0001$ level with an R^2 of 0.5571, an improvement of R^2 by 0.0004 over Model 3. Model 4 added in the CMOS proximity information and showed this variable was significant at the $p < 0.01$ level with an R^2 of 0.5573, which improved R^2 by 0.0002 over Model 3. A summary of these and of the models are shown in Table 4.

Table 4. Summary of Results

Variable	Sales price (logged) Model 1		Model 2		Model 3		Model 4	
Intercept	10.5700	***	3.2080	***	3.0830	***	3.1230	***
Property features								
Owner occupied property	0.5796	***	0.2510	***	0.2506	***	0.2509	***
Square footage of structure	0.0006	***	0.0005	***	0.0005	***	0.0005	***
Parcel size in feet^2 (logged)	-0.0983	***	0.1780	***	0.1895	***	0.1913	***
Age 0_50 years (1/0)	0.3254	***	0.4073	***	0.4044	***	0.4034	***
Age 51_80 years (1/0)	-0.1415	***	0.1435	***	0.1437	***	0.1450	***
Structural condition rating	0.2436	***	0.0422	***	0.0418	***	0.0425	***
Number of bathrooms	0.0072		-0.0047		-0.0037		-0.0037	
Social and economic information								
Population density			0.0000	***	0.0000	***	0.0000	***
Population median age			-0.0059	***	-0.0054	***	-0.0058	***
Median household income (logged)			0.6988	***	0.6997	***	0.6968	***
Families as a percentage of all households			-0.0171	***	-0.0169	***	-0.0167	***
Poverty rate in percent			-0.0050	***	-0.0051	***	-0.0053	***
Percentage of high school diploma or higher			0.0043	***	0.0040	***	0.0039	***
Unemployment rate			-0.0113	***	-0.0116	***	-0.0120	***
Vacancy rate			-0.0115	***	-0.0118	***	-0.0118	***
Number of years living (tenure) in CT			-0.0242	***	-0.0246	***	-0.0245	***
Crime rate			0.0041	***	0.0045	***	0.0041	***
Percentage of tree canopy			-0.0037	***	-0.0038	***	-0.0039	***
Park and CMOS proximity								
<0.25 mi or less distance to park (1/0)					0.0504	***	0.0482	***
<0.25 mi or less distance to CMOS (1/0)							0.0273	*
R^2	0.2387	***	0.5567	***	0.5571	***	0.5573	***
Change R^2			0.3180		0.0004		0.0002	

* p<.01, ** p<.001, ***p<0

Note: The control property is Age > 80 years. CT: Census tract

Multicollinearity, or relationships between independent variables can affect model performance. The model variables were checked for multicollinearity as indicated by the VIF of each variable. VIF scores are generally interpreted in ranges. If a VIF score is equal or close to 1, then there is no correlation between the variable and other variables in the model. A VIF score greater from 1 to 5 is considered minimally correlated. A score of 5 up to 10 is considered moderately correlated and a VIF of greater than 10 is considered highly correlated.

Table 5 shows the VIFs for the model variables. In Model 4, the VIFs for median household income and the poverty rate are 7.065 and 5.257, respectively. These data suggest both of these variables were moderately correlated in the model, but they were still below the VIF threshold of 10.

Table 5. Variance Inflation Factors by Variable and Model

	VIF			
Variable	Model 1	Model 2	Model 3	Model 4
Owner occupied property (1/0)	1.0329	1.1210	1.1210	1.1212
Square footage of structure	1.5537	1.7306	1.7321	1.7381
Parcel size in feet^2 (logged)	1.4316	2.7259	2.9592	2.9814
Age 0_50 years (1/0)	1.0252	1.0390	1.0395	1.0397
Age 51_80 years (1/0)	1.2787	1.5536	1.5536	1.5570
Structural condition rating (Best: 7- Lowest: 2)	1.3546	1.5538	1.5542	1.5581
Number of bathrooms	1.5584	1.5638	1.5649	1.5649
CT Population density (Number of people/mile^2)		1.5722	1.5731	1.6059
Population median age in years		1.5492	1.5615	1.5870
Median household income (logged)		7.0507	7.0511	7.0655
Families as a percentage of all households		2.0674	2.0831	2.1239
Poverty rate in percent		5.2172	5.2193	5.2570
Percentage of high school diploma or higher education		2.9969	3.0057	3.0201
Unemployment rate in percent		3.4034	3.4109	3.4409
Vacancy rate in percent		2.1176	2.1328	2.1334
Number of Years living (tenure) in CT		2.4230	2.4296	2.4315
Crime rate		2.2326	2.2499	2.3237
Percentage of tree canopy		2.8105	2.8237	2.8349
<0.25 mile or less distance to park (1/0)			1.2673	1.2754
<0.25 mile or less distance to CMOS (1/0)				1.3252

CT: Census tract

The coefficients for the parks and CMOS variables in this log-linear model can be interpreted as follows. The coefficient for park information was positive and 0.048. Since the dependent variable was the log function of sale price, the park proximity impact was:

(5) $$P_i(K_i=1)/ P_i(K_i=0) = e^{\delta} \approx 1 + \delta \text{ where } \delta = 0.048$$

Where P = Price and K = 1 when the property was < 0.25 mi distance to a park. In other words, if K increased by 1 unit, then P changed by 100 * δ percent approximately. Alternatively,

(6) $$\%\Delta P=100\cdot \delta \cdot\Delta K \quad \%\Delta P =4.8\%$$

Where P = Price and K = 1 when the property was < 0.25 mi to a park. Thus, when properties were within a quarter mile distance of a park, the park added 4.9% to the sale price of properties, all else equal, and this impact was at the significance level of 0.0001. The dollar impact was estimated, using the median house price of $124,000.

(7) $124,000 * 4.8% = $5,952.

This amount can be interpreted as the park added $5,952 to the sale price of a house within a quarter mile compared to a similar house farther away from a park.

The interpretation of the impact of CMOS information followed the same procedure. The coefficient for the CMOS variable was 0.027. Given the log-linear model, CMOS proximity impact was:

(8) $P_i(C_i=1)/ P_i(C_i=0) = e^{\delta} \approx 1 + \rho$ where $\rho = 0.027$

Where P = Price and C = 1 when the property was <0.25 mi to a CMOS. In other words, if C changed by one unit, then P changed by 100* ρ percent, approximately. Alternatively,

(9) $\%\Delta P=100\cdot \delta \cdot\Delta C \quad \%\Delta P = 2.7\%$

Where P = Price and C = 1 when a property was 0.25 mi distance to a CMOS. Thus, when a property was within a quarter mile of a CMOS, the CMOS added 2.7% to the house sale price, as else equal, and this impact was at the 0.01 significance level. The dollar impact was estimated using the median house price of $124,000 is as follows:

(10) $124,000 * 2.7% = $3,348

Thus, a CMOS added $3,348 to the sale price of a house within a quarter mile compared to a property beyond that distance.

Chapter 4: Discussion

The results of this study confirm that CMOSs had a positive economic effect on house sale prices. This study showed CMOSs added 2.7% to properties sold within a quarter mile. While not the focus of the central focus, this study also confirmed that parks added 4.8% to properties within a quarter mile. The premium for CMOSs was 2.1% lower than the park premium.

The difference between the two premiums may be attributed to differences in funding levels and amenities. CMOSs are typically funded either through grants, community donations or sweat equity and feature modest recreational and play amenities. Whereas, parks are funded via tax revenue though the city budget and can feature a wide range of active and passive use amenities. Given the amenity and funding level differences, the park premium of 4.8% can be viewed as the likely upper limit of the CMOS premium in Baltimore.

Comparing the CMOS premium of 2.7% with the literature, this study was 0.8% higher than that found by Voicu and Been (2008). Although the distance used in this study was 0.05 mile (264 feet) greater than the later study, this small reduction in distance would likely result in the same or slightly higher CMOS proximity premium based on Crompton's (2004) proximate principle. Thus, this study shows CMOSs in Baltimore added more value than community gardens in New York City.

To confirm this, future research could explore using a variety of distances to test the sensitivity of the CMOS sale premium to this choice.

However, the 4.8% park premium and the 2.7% CMOS premium found in this study is much lower than the 7% premium for small parks and 6% premium for medium parks found by Espey and Owusu-Edusei's (2001). The lower premium found for parks and CMOSs cannot be attributed to study distance differences since the study distance differed by only 0.03 mi. Rather, these differences likely result from fundamental difference between Baltimore and Greenville, SC, the location of the Espey and Owusu-Edusei study.

In terms of crime, this study showed a slightly positive relationship between crime and sale prices (γ=0.0041), which contradicted the relationship shown by Troy and Grove (2008). This result was likely due to the study's design. Because the crime rate was considered at the census tract level, the localized impact of crime locations on house sale prices was likely obscured due to smoothing of the data. Future research could refine the design to better incorporate crime impact on park and CMOS proximity in the model.

In terms of the open greenspace literature, this study's findings were 2.63% higher for CMOSs and 4.1% for parks than that of Conway, Li, Wolch, Kahle and Jarret's (2010) modest premium of 0.07% in inner city Los Angeles. The distance in the later study was 0.17-0.19 mi shorter than this study. By the proximate principle, the CMOS premium in this study would be expected to be higher at the shorter distance, assuming the crime threshold does not exceed the level to create a negative relationship between these amenities and proximity to them. Open greenspace therefore seems to represent the minimum price premium for CMOSs and house buyers valued CMOSs much higher than general open space.

This research could be further refined by increasing the number of years in the study, which would be better able to incorporate economic cycles over time. Cho, Kim, & Roberts (2011) show demand for environmental amenities declined during the 2008 recession compared to the 200-2006 real estate boom. A follow-on study of a longer time period could help identify if the sale price premiums for CMOSs and parks found in this study were a function of the economic conditions during the study period or if they reflect an average premium over the economic cycle.

Another improvement to this study could be made by incorporating park and CMOS size and use information in the model. This information could shed light on the impact of passive versus active use as well as the size and design for parks and CMOSs. This information would be particularly helpful to guide planners and community organizations as they manage existing and create new CMOSs and parks in the future.

Finally, this study sets the foundation for a future study to compare the economic impact of alternative land uses (e.g., vacant lots, parks, CMOSs, forest patches and other open greenspaces) on house sale prices in Baltimore. By comparing a sample of census tracts with high and low vacancy rates to control for overall real estate demand, the sale price premiums for each type of land use under these two demand scenarios could be identified. As the planners and community members invest in addressing the thousands of vacant lots in Baltimore, this future study could guide decision-makers as they select the most appropriate strategy given the underlying real estate market conditions.

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