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分析綠地對巴爾的摩市財產犯罪率的影響

Analyzing the Effect of Green Space on Property Crime Rates in Baltimore City

李每喜

Mariah Campbell

指導教授: 劉鋼 博士

Advisor: Kang Liu Ph.D.

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Analyzing the Effect of Green Space on Property Crime in Baltimore City

The undersigned, appointed by the Department of Agricultural Economic, College of Bioresources and Agriculture on June 11th, 2025 have examined a Master's Thesis entitled above presented by Mariah Campbell (Student ID: R12627028) candidate and hereby certify that it is worthy of acceptance.

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摘要

本論文檢視了2011年至2021年巴爾的摩市綠地與財產犯罪之間的關係，特別關注綠地維護和社區收入水準如何影響這種關係。研究借鑒了環境設計預防犯罪、破窗效應和隱瞞假說等理論，探究維護綠地是否真的有助於減少犯罪，以及這種效果在富裕社區和低收入社區是否有所不同。該研究使用來自55個社區統計區域的面板數據，建立了固定效應回歸模型，檢驗了維護和未維護的綠地與財產犯罪隨時間的變化關係。維護良好的綠地通常與較低的犯罪率相關，但在大多數模型中，這種關係並不具有統計顯著性。收入是降低財產犯罪率更顯著且更一致的預測因子。我們使用了交互項來檢驗收入是否會增強綠地的影響，但數據並未明確支持這一觀點。視覺化地圖顯示，雖然自2011年以來，全市綠地維護規模已擴大，但成長幅度並不均衡。有些地區的維護活動大幅增加，而其他地區則基本保持不變。這些模式表明，獲得綠地改善的機會仍取決於居住地。研究結果揭示了一個比理論本身更複雜的圖像。綠地固然有價值，但它並非孤立運作。在一個長期不平等的城市中，如果沒有更廣泛的結構性支持，綠化工作的角色就會受到限制。

關鍵字:綠地、犯罪、巴爾的摩

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Abstract

This thesis examines the relationship between green space and property crime in Baltimore City between 2011 and 2021, with special attention to how green space maintenance and neighborhood income levels may shape that relationship. Drawing from theories like Crime Prevention Through Environmental Design, Broken Windows, and the Concealment Hypothesis, the research asks whether keeping green spaces maintained actually helps reduce crime, and whether that effect looks different in wealthier versus lower-income communities. Using fixed-effects regression models on panel data from 55 Community Statistical Areas, the study tests how maintained and unmaintained green spaces relate to property crime over time. Maintained green space was generally linked with lower crime, but this relationship was not statistically significant in most models. Income stood out as a stronger and more consistent predictor of lower property crime. An interaction term was used to see if income made the effects of green space stronger, but the data did not clearly support that idea. Visual maps show that while green space maintenance has expanded across the city since 2011, the growth has not been equal. Some areas saw major increases in maintenance activity, while others remained largely untouched. These patterns suggest that access to green space improvements still depends on where someone lives. The results point to a more complicated picture than what theory alone suggests. Green space has value, but it does not operate in isolation. In a city shaped by long-standing inequalities, the role of greening efforts is limited without broader structural support.

Keywords: green space, crime, Baltimore

JEL Codes: Q51, R14, K42

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Chapter 1 Introduction

1.1 Motivation and Background

Urban green spaces have evolved from aesthetic features into vital elements of city infrastructure. These spaces are frequently associated with improved mental health, stronger social connections, and better environmental conditions (Jennings & Bamkole, 2019). More recently, green spaces have been examined as possible tools for crime reduction (Kvit et al., 2022). However, the strength and direction of this relationship are still widely debated. While many studies suggest green space can help reduce crime, especially when well-maintained, others find little impact or even the opposite effect (Shepley et al., 2019). Some studies found that greenery may offer cover for criminals or signal neglect if it is not well maintained (Wilson & Kelling, 1982). These mixed findings often come down to context: what works in one neighborhood may not work in another, and the presence of green space alone does not guarantee safety. How it is maintained, how it is used, and who it is meant to serve all shape its impact (Kondo et al., 2018).

Baltimore provides a compelling setting to explore this issue. Once a prominent industrial center, the city has endured decades of disinvestment, structural racism, and unequal urban development. These forces have contributed to consistently high property crime rates. In 2015, Baltimore's property crime rate peaked for that decade with 4,980.4 property crimes per 100,000 people (Macrotrends, n.d.). Although crime rates have slightly improved since 2019 with 135 fewer property crimes per 100,000 residents from 2019 to 2020 (Police Executive Research Forum*, 2020*), many communities continue to face high vacancy levels, housing instability, and underinvestment in public infrastructure (Baltimore City Department of Planning, 2020).

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To address these challenges, the city has implemented a range of greening strategies. Initiatives like Adopt-A-Lot, Project Vital, and the Baltimore Green Network have transformed vacant land into functional green spaces used by the community. These efforts have been reinforced by broader policy changes, such as the 2013 Urban Agriculture Plan, sustainability updates in 2019, and tax incentives that encourage urban farming. These interventions are designed to turn abandoned spaces into assets that support community well-being. Still, an open question remains: Can the presence of green space actually reduce property crime, and how do factors such as upkeep and income levels alter this dynamic?

Several criminological theories offer useful frameworks for investigating this question. Crime Prevention Through Environmental Design (CPTED) emphasizes the importance of visibility, territorial control, and physical upkeep in deterring crime (Cozens & Love, 2015). Broken Windows Theory argues that visible neglect, including overgrown vegetation or debris, sends a signal that an area lacks oversight and may encourage further crime (Wilson & Kelling, 1982). The concealment hypothesis builds on this by warning that dense, poorly maintained vegetation can limit visibility and unintentionally create spaces that shield criminal activity (Nassauer et al., 2014). Together, these theories suggest that it is not only the presence of green space that matters, but the way that space is managed and perceived by the community.

1.2 Research Objectives

This thesis examines the relationship between maintained green spaces and property crime in Baltimore City, using data collected from 2011 to 2021. The analysis focuses on how long-term patterns in property crime vary across the city's 55 Community Statistical Areas (CSA's) which are census tract boundaries used for

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demographic analysis. This research focuses on the influence of green space upkeep, assessing whether maintained areas are linked to reduced crime and exploring how this relationship may vary depending on neighborhood economic conditions.

A core objective is to understand how socioeconomic conditions, particularly income levels within each CSA, interact with green space interventions. The study also engages with several criminological theories, CPTED, Broken Windows Theory, and the concealment hypothesis, to explore how physical design and upkeep influence community safety.

By investigating these patterns, the research contributes to broader discussion about environmental justice, urban safety, and equitable city planning. It aims to provide insight into when and where green space investments are most effective, and what conditions are necessary for those investments to translate into real community benefits.

1.3 Research Hypotheses

Based on a constructive review of previous literature, this thesis seeks to empirically test the following three hypotheses:

H1: CSAs with higher levels of maintained green space will be associated with lower property crime rates compared to CSAs with less or poorly maintained green space.

H2: In low-income CSAs, unmaintained green space will be associated with higher property crime rates.

H3: The crime-reducing effects of maintained green space will be stronger in medium to high income CSAs than low income CSAs.

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Chapter 2 Literature Review

2.1 Theoretical Foundations Linking Green Space and Crime

Urban green space has become a recurring subject in research related to public safety and community resilience (Shepley et al., 2019). Among the most influential frameworks is Crime Prevention Through Environmental Design (Jeffery, 1971). This theory argues that public space, when thoughtfully designed and consistently maintained, can shape behavior in ways that discourage crime. Key elements of this approach include natural surveillance, restricted access, and the physical signals that suggest ownership and care. Newman (1972) later expanded on these ideas through his study on defensible space, which emphasized features like lighting, fencing, and clear pathways as tools for reinforcing community oversight.

Another prominent framework is Broken Windows Theory (Wilson & Kelling, 1982). This theory focuses on the visual condition of the urban environment, suggesting that signs of neglect—such as litter, graffiti, or overgrown lots—can signal to others that a space is unmonitored. In this way, physical disorder may act as a cue that encourages further antisocial behavior. The theory builds on CPTED by highlighting the social meaning of visible decay and the ways it undermines informal social control.

The Concealment Hypothesis introduces a different, but complementary, perspective. While CPTED and Broken Windows focus on human cues and social order, this hypothesis centers on how vegetation itself may affect visibility. Overgrown or dense greenery can block sightlines, creating blind spots that offer cover for illicit activity. In contrast to maintained green space, which is designed to be open and navigable, unmaintained space may unintentionally foster conditions that make crime more likely (Troy et al., 2012).

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Each of these theories contributes to the rationale behind this thesis. H1 examines whether the presence and visibility of maintained green space are linked to reduced levels of property crime. H2 draws from Broken Windows and the Concealment Hypothesis to explore whether unmaintained green space in low-income communities may lead to increased crime. H3 addresses how the benefits of maintenance vary across income levels, recognizing that not all communities have equal capacity to manage or benefit from greening efforts.

2.2 Research on Green Space Design and Crime Reduction

Empirical studies offer support for these theories, though the findings vary by setting. A 2019 review by Shepley and colleagues examined dozens of urban greening projects and found a general connection between well-maintained green spaces and lower crime (Shepley et al., 2019). Spaces that featured good lighting, clear pathways, and community use were associated with safety. The authors noted that gardens and shared open spaces could build community trust and increase informal surveillance. However, they also cautioned that neglected or overgrown spaces could do the opposite, increasing the potential for crime by contributing to a sense of disorder and providing opportunities for concealment. These insights speak directly to H2, which anticipates that unmaintained green space may elevate property crime risk in low-income areas.

Additional depth comes from Taylor's 2018 spatial analysis of urban gardens in Minneapolis. His study found that the quality of maintenance had a direct impact on crime rates. Where gardens were regularly cared for, nearby property crime decreased (Taylor, 2018). His findings lend support to both CPTED and the Concealment Hypothesis, reinforcing the idea that maintenance is not just aesthetic but functional in terms of public safety. Taylor also observed that wealthier neighborhoods saw smaller

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reductions in crime following green space improvements. This finding helped inform H3 of my thesis, which proposes that income levels shape how much benefit communities receive from maintained green space.

Frazier and Jung's 2023 research on community gardens in Seattle further supports this connection (Frazier & Jung, 2023). Their eleven-year long analysis revealed that well-kept gardens reduced property crime, particularly after a few years had passed. Residents reported that the gardens helped strengthen community bonds and encouraged vigilance. Interestingly, the researchers found that lower-income neighborhoods saw greater reductions in crime compared to higher-income areas. These results suggest that greening initiatives may be most effective in disinvested communities when the spaces are properly maintained and actively used. Frazier and Jung's (2023) eleven-year long timeframe and attention to neighborhood context directly shaped the decision to also use an eleven-year panel for my current research.

2.3 When and Where Green Space Does Not Help

While many studies find positive effects, not all research agrees that green space reliably reduces crime. A 2008 study by Troy and Grove examined the relationship between green space and property crime in Baltimore (Troy & Grove, 2008). They found that the benefits of green space were strongest in middle-income areas. Maintained greenery tended to reduce crime, but overgrown or neglected vegetation had the opposite effect. These findings are consistent with CPTED, Broken Windows Theory, and the Concealment Hypothesis. They also support the H2 in this thesis by showing that maintenance plays a decisive role in determining whether green space acts as a crime deterrent or a risk factor.

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A 2021 study by the USDA Forest Service, focused specifically on Baltimore, found that a 10 percent increase in tree canopy was linked to a 12 to 15 percent reduction in property crime (Troy et al., 2012). Their study emphasizes the importance of ongoing maintenance. Trees and vegetation that preserved visibility while offering aesthetic and environmental benefits were associated with safer communities. These effects were again most noticeable in middle-income neighborhoods. Their study's Baltimore-specific findings further support the decision to treat income levels as a key moderating variable, in line with H3.

2.4 Lessons from Baltimore: What the Local Data Tells Us

Several studies focused on Baltimore offer insights that ground this thesis in local conditions. One of the most relevant evaluations of Baltimore's greening efforts comes from a study of the Care-A-Lot (CAL) program, which funds local community groups to maintain and beautify vacant lots (Kvit et al., 2022). The study followed over 2,300 lots from 2016 to 2019, comparing neighborhoods that participated in CAL to similar neighborhoods that did not. The results were clear: blocks with CAL-maintained lots saw larger declines in both property and violent crime than blocks that went untreated (Kvit et al., 2022). The strongest reductions were observed closest to the greened lots, and especially in areas with high vacancy and long-term disinvestment.

What made the difference wasn't just the presence of green space, it was how consistently those lots were maintained and whether that care was visible. One-time cleanups had weaker effects. In contrast, regularly mowed, landscaped, and visibly cared-for lots saw sharper reductions in crime (Kvit et al., 2022). These findings mirror the broader pattern in this thesis: greening alone does not change neighborhood conditions unless it is paired with sustained investment and stewardship. In many ways,

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the CAL study reinforces the argument that green space operates not just as a physical feature, but as a social signal.

Unlike prior work that often grouped all green interventions together, this study focuses on how actively used, visibly maintained space differs from unmonitored or overgrown lots.

2.5 Contribution of This Thesis

The existing literature largely agrees that green space can influence crime rates, but how, where, and under what conditions remain key questions. Many earlier studies combine different types of crime or focus on a single moment in time. This thesis contributes by narrowing the scope to property crime alone and using panel data from 2011 through 2021. The goal is to evaluate whether the condition of green space, specifically whether it is maintained, matters more than its presence alone.

Through this approach, the study tests three hypotheses rooted in theory and informed by existing evidence. H1 expects that maintained green space will correlate with reduced crime. The second explores whether unmaintained space, particularly in low-income communities, may have the opposite effect. The third examines whether income level alters the relationship between green space and crime, reflecting growing evidence that greening outcomes are shaped by local economic context.

By anchoring the analysis in Baltimore's diverse and divided urban landscape, this research adds nuance to the debate over whether green space can function as a reliable public safety strategy and identifies the conditions under which it is most likely to succeed.

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Chapter 3 Data and Variables

3.1 Data Sources and Variable Explanations

The geographical boundaries are based on the official 55 CSAs of the Baltimore Neighborhood Indicators Alliance (BNIA). The BNIA clustered Baltimore City's 270+ neighborhoods into CSAs to align with the census tracts. The CSAs have changed over time, there are a few that have changed between the 2010 Census and the 2020 Census. In my study, I use the CSA outlined in the 2020 Census as referenced in Figure 3.1.

Figure 3.1

Baltimore City Community Statistical Area 2020

Note. Data Source: BNIA.

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Table 3.1 outlines the key variables used in my thesis, including how each is defined, measured, categorized, and sourced. The primary independent variable, Maintained green space (*maintained*), is a count measure showing whether a green space is intentionally managed. The dependent variable, Property Crime Rate (*crime_rate*), reflects the number of property crime arrests per 1,000 residents in each CSA. Control variables include Median Household Income (*MHI*), Racial Diversity Index (*RDI*), Vacant Building Notices (*vac_rate*), High School Completion Rate (*HSCR*), Population Under 18 (*pct_under*), and *unemployment*. Each variable is selected to account for structural, demographic, or environmental conditions that could shape crime outcomes.

Table 3.1

Descriptions, Units, and Sources of Variables

Variable	Description	Units	Type of Variable	Source
Property Crime Rate (*crime_rate*)	Arrests per CSA that meet the Baltimore definition of property crime	Per 1,000 residents	Dependent	Open Baltimore
Maintained Green Space (*maintained*)	Count of Intentionally and actively managed urban farms, community gardens, pocket parks, and urban forests in a CSA	Number of sites	Independent	Project VITAL
Green Space (*greenrate*)	Count of urban farms, community gardens, pocket parks, and urban forests actively or not actively managed in a CSA	per 1,000 residents	Independent	Project VITAL
Median Household Income (*MHI*)	Middle value of household earnings in a CSA	USD ($1000)	Control / Interaction	Open Baltimore

(Table Continues)

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Table 3.1, Continued

Variable	Description	Units	Type of Variable	Source
Income Category (*low*)	indicator equal to 1 if low-income CSA and 0 if medium/high CSA	Binary variable indicating CSA income group. "Low" = lowest quartile of median household income; "Medium/High" = all others.	Moderator in Model 3	Open Baltimore
Racial Diversity Index (*RDI*)	Probability that two randomly selected individuals in a CSA belong to different racial/ethnic groups	% (0% = no diversity, 100% = fully diverse)	Control	BNIA
Vacant Building Notices Rate (*vac_rate*)	Number of vacant building notices reported in a CSA	Per 1,000 residents	Control	Open Baltimore
Population Under 18 (*pct_under*)	Total number of residents under age 18 in a CSA	Number of people	Control	ACS
High School Completion Rate (*HSCR*)	Percentage of 12th graders who completed high school in a given year	%	Control	Open Baltimore
Unemployment Rate (*unemployment*)	Percentage of individuals aged 16–64 in the labor force but not currently working	%	Control	Open Baltimore

The *crime_rate* variable originates from the Open Baltimore dataset "Property Crime Rate per 1,000 Residents - Community Statistical Area." Property crime is defined by the FBI as burglary, arson, motor vehicle theft, and larceny the (Federal Bureau of Investigation, 2020). The dataset is GIS coded, providing both spatial and

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descriptive information of the crime rate for the years 2011 to 2023, filtered to years 2011 to 2021 to correspond with the green space dataset. The information extracted from the dataset include geocoded CSAs, property crime rate and years. This dataset was used for identifying and displaying the distribution of property crime by CSA and provides the dependent variable in modeling the relationship between *crime_rate* and *maintained*.

Maintained is defined as "intentionally and actively managed urban farms, community gardens, pocket parks, and urban forests" (Baltimore Green Space, n.d.-a). These definitions align with Baltimore City's Zoning Code descriptions of urban agriculture, community-managed open-space gardens, and community-managed open-space farms. Urban agriculture refers to the "cultivation, processing, and marketing of food, with a primary emphasis on operating as a business enterprise" (Baltimore Green Space, n.d.-a). A community-managed open-space garden is defined as "traditional community-garden activities of planting, cultivating, harvesting, maintaining, and distributing fruits, flowers, vegetables, or ornamental plants" (Baltimore Green Space, n.d.-a). If an open-space garden additionally keeps livestock and animals, operates temporary farm stands, or freely redistributes organic waste material for composting, it is classified as an open-space farm.

Greenrate is defined as "urban farms, community gardens, pocket parks, and urban forests" (see table 3.1). *Greenrate* is an independent variable displaying maintained and neglected green space. It is calculated as a rate per 1,000 residents in each CSA. While *greenrate* is not included as a predictor in the regression models, it is used in the descriptive analysis to provide context for interpreting the maintained variable and other results. Including *greenrate* in the summary statistics allows for a clearer comparison between communities and illustrates broader patterns of green space

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availability that help situate the regression findings. Meanwhile, *maintained* is the primary independent variable in this study. *Maintained* variable represents the raw number of green space sites classified as actively managed within each CSA. It is a count measure derived from the broader *greenrate* variable, which quantifies the total area of vegetated public space within each CSA in Baltimore City. Maintained sites include urban farms, community gardens, pocket parks, and urban forests with evidence of regular upkeep, such as mowing, landscaping, or structural improvements. Both variables originate from the Project VITAL dataset (Baltimore Neighborhood Indicators Alliance–Jacob France Institute, n.d.), which provides spatially coded information on green space features across the city. For this research, shapefiles were aggregated to the CSA level and paired with annual demographic and crime data from 2011 to 2021 to allow for longitudinal analysis. Across all CSAs and years, *maintained* ranges from 0 to 108 sites, with a mean of 4.3 sites, reflecting substantial variation in the distribution of maintained green space across the city.

MHI data came from the Open Baltimore resource "Median Household Income – Community Statistical Area." This dataset contains GIS-coded information, which provides both spatial boundaries for each CSA and descriptive statistics on income levels. The time span runs from 2010 to 2023, but for consistency with the other variables used in this study, only data from 2011 to 2021 were included. All values are inflation-adjusted using the American Community Survey five-year estimates (Baltimore Neighborhood Indicators Alliance, n.d.-b). For instance, income figures from 2007–2011, 2008–2012, 2009–2013, and 2016–2021 correspond to 2011, 2012, 2013, and 2021 dollars, respectively.

From this dataset, I used the geocoded CSA identifiers, the *MHI* values, and the corresponding years. To create the income groupings, the dataset was first cleaned and

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limited to the 2011–2021 period. The *MHI* for each CSA was then averaged across those years, producing a single long-term income estimate (expressed in \$1,000s) that reflects the general economic conditions over the decade. Using these CSA-level averages, a quantile analysis was carried out to identify the 25th and 75th percentiles (FasterCapital, 2025). The first quartile (Q1) was approximately 34.1 (\$34,122) and the third quartile (Q3) was approximately 56.5 (\$56,522). CSAs with average incomes below Q1 were classified as low-income, those above Q3 as high-income, and those in between as medium-income.

Low was derived from the same "Median Household Income – Community Statistical Area" dataset used to construct the continuous *MHI* variable. For each CSA, the long-term average median household income over the 2011–2021 period was calculated (see *MHI* description). Communities with average incomes below Q1 were classified as low-income and assigned a value of 1 in the binary variable, while those at or above Q1 were classified as medium/high-income (*MH*) and assigned a value of 0. This coding allows for direct comparison of maintained green space effects between low-income CSAs and all other CSAs in Model 3.

RDI originates from the Open Baltimore dataset "RDI - Community Statistical Area." The index does not indicate which race/ethnicity is most prominent in a CSA. It measures the diversity of a population. The dataset is GIS coded, providing both spatial and descriptive information of the *RDI* for the years 2010 to 2023, filtered to years 2011 to 2021 to correspond with the previous datasets. The dataset is inflation-adjusted using the ACS 5-year estimates, following the same structure as the *MHI* dataset. The information extracted from the dataset include geocoded CSAs, *RDI* and years. This dataset was used for identifying and displaying the distribution of the *RDI* by CSA and

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provides a control variable for modeling the relationship between *crime_rate* and *maintained*.

Pct_under variable is retrieved from the Baltimore City Census Comparison: 2010-2020 - by Neighborhood Statistical Area (NSA). This dataset was extracted from the official 2020 Decennial Census and 2010 Decennial Census by the Baltimore's Department of Planning. The dataset contains total population, population under 18, and other demographic variables from the 2010 and 2020 census. I extrapolated the population size for all variables between the two census years using intercensal population estimates (U.S. Census Bureau, n.d.). I used the same method to extrapolate the population size for the year 2021 using the same method. The *Pct_under* variable was computed by taking the difference between total population and population over 18. This dataset uses NSA as opposed to CSA. I combined the NSA's into CSAs in accordance with Baltimore city guidelines. This dataset was used for identifying and displaying the distribution of *pct_under* by CSA and providing control variables for modeling the relationship between *crime_rate* and *maintained.*

Vac_rate originates from the Open Baltimore dataset "Vacant Building Notices - Community Statistical Area." The master database is GIS coded, providing both spatial and descriptive information of historical and current vacant building notices in Baltimore City. It is updated on a daily basis and filtered from 2011 to 2021 for my dataset. The information extracted from the dataset include geocoded CSAs, address, vacant building notices and years. I calculated the amount of vacant notices in each CSA and then used the total population variable to create the vacant notices per 1000 residents variable. This variable is an additional control variable used to refine the model depicting the relationship between *crime_rate* and *maintained*.

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HSCR variable comes from the "High School Completion Rate – Community Statistical Area" dataset. It measures the percentage of 12th-grade students who successfully completed high school within a given school year, calculated out of all 12th graders residing in a specific CSA. The dataset is GIS-coded, allowing it to capture both spatial and descriptive dimensions of educational attainment in Baltimore City. It spans from 2010 to 2021, but for the purposes of this analysis, it was filtered to cover only 2011 to 2021. High school completion rate was used as a control variable to refine the model and better isolate the relationship between *maintained* and *crime_rate*. Educational attainment often reflects deeper patterns of neighborhood stability, institutional investment, and long-term opportunity which are factors that shape both crime risk and community capacity to maintain public space.

Unemployment originates from the "Unemployment Rate - Community Statistical Area." This variable represents the share of individuals aged 16 to 64 who are part of the labor force—actively seeking employment—but remain unemployed (Baltimore Neighborhood Indicators Alliance, n.d.-c). The master database is GIS coded, providing both spatial and descriptive information of historical and current unemployment rate in Baltimore City. It provides data for the years 2006 to 2023 and is filtered from 2011 to 2021. This variable is an additional control variable used to refine the model depicting the relationship between *crime_rate* and *maintained*.

3.2 Accounting for Pandemic Effects

The COVID-19 pandemic brought about major social and economic changes in Baltimore starting in 2020, changes that likely shaped both patterns of property crime and how residents interacted with green space. Instead of creating a single pandemic indicator, this study uses a two-way fixed effects approach to account for differences

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that remain constant within each CSA and for events that vary from year to year. The CSA effects control for enduring local characteristics, such as long-standing economic conditions, the physical layout of neighborhoods, and historical land use, while the year effects capture broader citywide or national shifts, including the arrival and progression of COVID-19, major policy changes, and wider economic trends. This method allows pandemic-related influences to be accounted for indirectly, avoiding the risk of redundancy or collinearity from a dedicated COVID variable, while focusing on changes in green space maintenance and other factors within each CSA over time.

3.3 Summary Statistics

Table 3.2 summarizes the descriptive statistics for the variables included in the regression analyses. These figures outline the distribution, variability, and range for each measure in the dataset, which encompasses 55 CSAs in Baltimore over the period 2011–2021.

Table 3.2

Summary Statistics of Key Variables

Variable	Units	Mean	Std	Min	Max
crime_rate	per 1,000 residents	46.27	27.69	7.6	266.5
maintained	Number of sites	4.33	11.49	0.0	108.0
greenrate	per 1,000 residents	1.60	4.20	0.0	32.5
MHI	$1,000s	48.72	27.56	13.5	135.4
low	binary	0.27	0.45	0.0	1.0
RDI	Index (0–100)	39.16	21.66	5.5	94.2
pct_under	%	20.85	6.02	4.3	35.1
vac_rate	Per 1,000 residents	1.26	5.68	0.0	70.6
HSCR	%	78.33	7.63	33.3	100.0
unemployment	%	11.28	6.38	1.1	30.1

Note. Sample size = 605.

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The dependent variable, *crime_rate*, measures property crimes per 1,000 residents. The mean is 46.3, with values ranging from 7.6 to 266.5. This large spread reflects the spatial concentration of crime in certain CSAs, a key dynamic explored in the models. *MHI* has an average of $48,721, with a wide range from $13,478 to $135,435, highlighting the economic disparities between CSAs. This variation is central to H3, which examines whether the effects of green space maintenance differ by income level. The *low* variable is a binary indicator equal to 1 if a CSA's long-term average MHI was below the first quartile (Q1 ≈ $34,122) and 0 otherwise. The mean of 0.27 indicates that about 27% of CSA–year observations are classified as low-income, providing the basis for subgroup comparisons in Model 3.

The primary independent variable, *maintained*, represents the raw count of green space sites classified as actively managed in each CSA. The mean of 4.3 indicates that, on average, each CSA had about four maintained sites per year, though the standard deviation of 11.5 and a maximum of 108 show that the distribution is highly uneven. This variation reflects large differences in greening efforts across the city, which is central to testing whether the number of maintained sites is associated with property crime rates.

The *greenrate* variable captures the total area of all public vegetated spaces, standardized per 1,000 residents. The mean of 1.6 and a wide range from 0 to 32.5 suggest that while some CSAs have extensive green space relative to their population, others have very little. This measure provides context for interpreting the role of *maintained* within the broader greenspace network.

RDI averages 39.2 on a scale from 0 to 100, with values ranging from 5.5 to 94.2. This indicates substantial variation in racial composition across neighborhoods, an important factor in urban sociology research and a control variable in the models.

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Pct_under averages 20.9 percent, ranging from 4.3 to 35.1 percent. This demographic measure controls for differences in age composition that may influence crime rates. The *vac_rate* averages 1.3 per 1,000 residents but reaches as high as 70.6 in some CSAs. High vacancy rates are often linked to disorder and reduced informal surveillance, consistent with the Broken Windows Theory and the Concealment Hypothesis (Troy & Grove, 2008). *HSCR* is relatively high, with a mean of 78.3 percent, but ranges from 33.3 to 100 percent, reflecting disparities in educational attainment across the city. Unemployment averages 11.3 percent, with a range from 1.1 to 30.1 percent. Higher unemployment levels may be associated with increased economic strain, which can influence crime patterns (Troy & Grove, 2008).

Together, these summary statistics highlight the substantial heterogeneity across Baltimore's CSAs in terms of green space availability and maintenance, socioeconomic status, and demographic composition. This variation provides the necessary context for testing the study's three hypotheses, particularly the expectation that maintained green space interacts with neighborhood income to influence property crime outcomes.

The visualization of key statistics provides necessary context for understanding the regression models used in Chapter 5, while also supporting the theoretical grounding discussed earlier. Each figure was chosen to show how conditions on the ground such as population structure, vacancy, education, and greening patterns interact with property crime and shape the outcomes this thesis seeks to explain.

Figure 3.2 uses the *greenrate* variable to show the unequal spatial distribution across CSAs. West and Central Baltimore CSAs such as Upton Druid Heights, Belair-Edison, and Southwest Baltimore display some of the highest rates of green space per capita. These are also areas with elevated vacancy and structural

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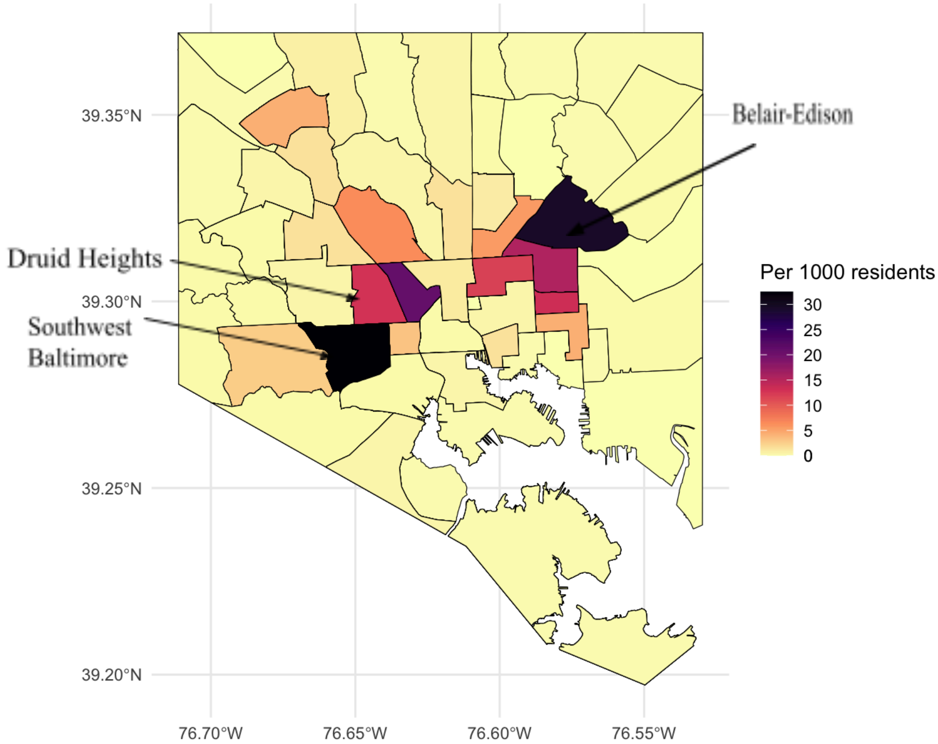
disinvestment, suggesting that greening efforts have been concentrated in neighborhoods with the most visibly abandoned land.

Figure 3.2

Rate of Average Greenspace per 1000 Residents by CSA (2011-2021)



Note. Data source: Project VITAL; map created in R.

In contrast, South and Southeast Baltimore generally exhibit lower per capita green space. This likely reflects a lower density of vacant parcels rather than a lack of formal green amenities like parks. Additionally, some CSAs appear in gray, indicating missing or unrecorded data during the study period. These gaps are concentrated around the edges of the city, where maintenance records or classification of lots may have been inconsistent or incomplete.

This figure highlights a central tension explored in this thesis: while green space can support environmental and public safety goals, its spatial presence alone does not

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guarantee benefits. Many of the neighborhoods with the most green space are also those experiencing the highest levels of crime and economic distress. Understanding how the quality, maintenance, and social context of that green space interact is essential for interpreting its potential to reduce property crime — a relationship tested in the models that follow.

Figure 3.3 shows the property crime rate in Baltimore averaged over the time period of 2011 to 2021. The trend was largely stable until 2019, followed by a notable decline in the last few years of the study period. This decline may be tied to several overlapping factors. In Baltimore, predominantly Black and low-income neighborhoods have historically experienced over-policing and surveillance—patterns that federal investigations have labeled as systemic and racially biased (Department of Justice, 2016). Shifts in local policing strategies could partly explain the recent drop in crime, especially if enforcement practices became less aggressive in certain areas. Broader population changes may also play a role, along with external shocks like the COVID-19 pandemic. During the early years of the pandemic, cities across the U.S. saw similar declines in reported crime and arrests, suggesting that both institutional and environmental disruptions likely influenced short-term patterns (Boman & Gallupe, 2020). Regardless, it underscores the importance of considering temporal trends in any discussion of green space interventions.

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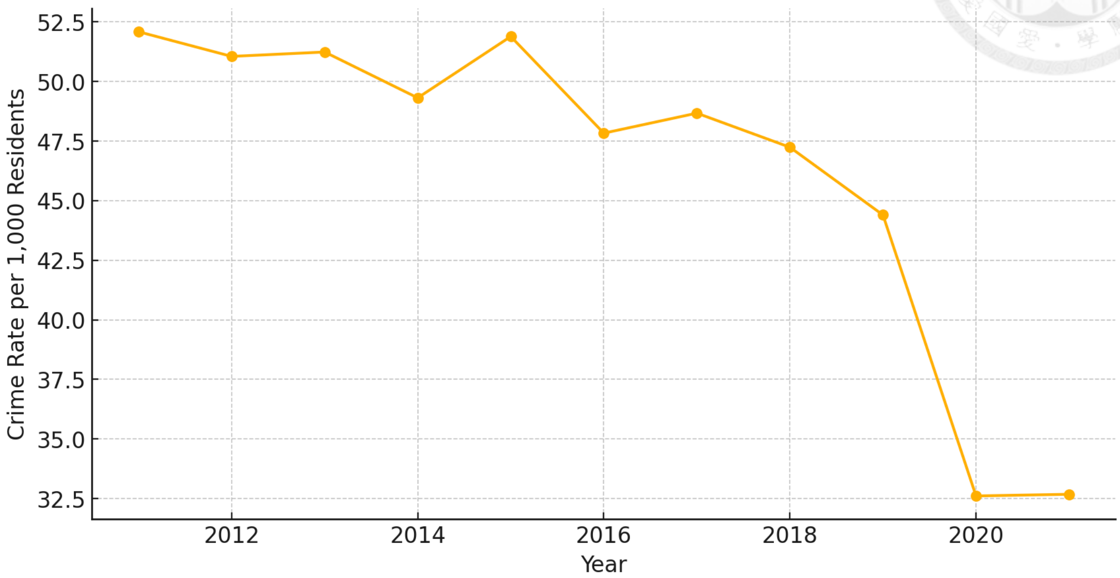
Figure 3.3

Average Property Crime Rate in Baltimore City (2011-2021)



Note. Data source: Open Baltimore; chart created in R.

Figure 3.4 shows the distribution of property crime rates across CSAs in a given year. As the map illustrates, property crime is not evenly distributed throughout the city. Central and southwestern CSAs, including communities around the downtown core and West Baltimore, experience the highest rates—some exceeding 57 property crimes per 1,000 residents. In contrast, the northern and southeastern corners of the city report comparatively lower rates, with several CSAs falling below 30 incidents per 1,000 residents. These spatial patterns align with long-standing structural inequalities in the city, where historically disinvested and predominantly Black neighborhoods tend to face higher levels of crime and enforcement.

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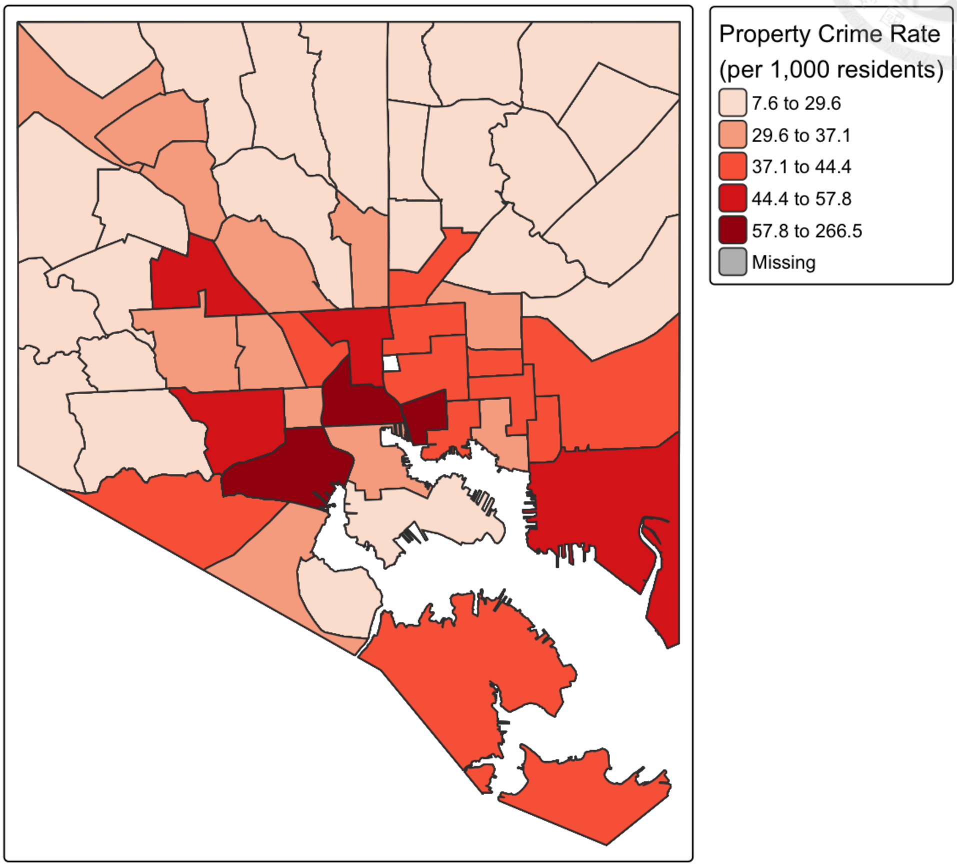
Figure 3.4

Average Property Crime Rate by CSA in Baltimore City



Note. Data source: Open Baltimore; visualization created in R.

Figure 3.5 reveals clear spatial differences in both the strength and direction of the correlation. Several CSAs, concentrated in South Baltimore and parts of the West, display moderate to strong negative correlations, with darker blue shading indicating values approaching –0.6. In these areas, increases in maintained green space are more strongly associated with reductions in property crime. In contrast, portions of Northwest Baltimore and pockets in the East show weak or even positive correlations, with deeper red tones indicating values above +0.4, suggesting that in these neighborhoods, higher levels of green space are not linked with lower crime and may even correspond to higher rates.

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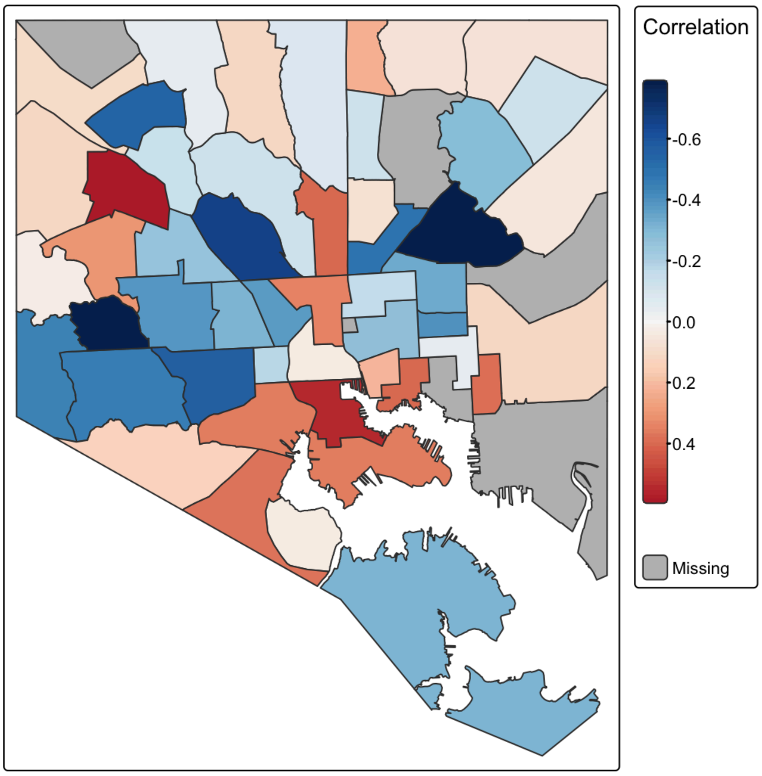
Figure 3.5

Correlation of Green Space and Crime by CSA



Note. Data source: Project VITAL and Open Baltimore; visualization created in R.

The spatial patterns in figure 3.5 align loosely with broader socioeconomic conditions. Higher-income CSAs, which often have greater neighborhood stability, stronger community organizations, and more consistent investment in park maintenance and programming, tend to appear in the blue range. In these areas, green space may function as an actively used and socially monitored public asset that strengthens community ties and discourages criminal activity. Conversely, lower-income CSAs in the red range may have green spaces that are inconsistently maintained, underused, or perceived as unsafe, reducing their potential crime-prevention benefits and, in some cases, allowing them to become sites for illicit activity. This reinforces the idea that

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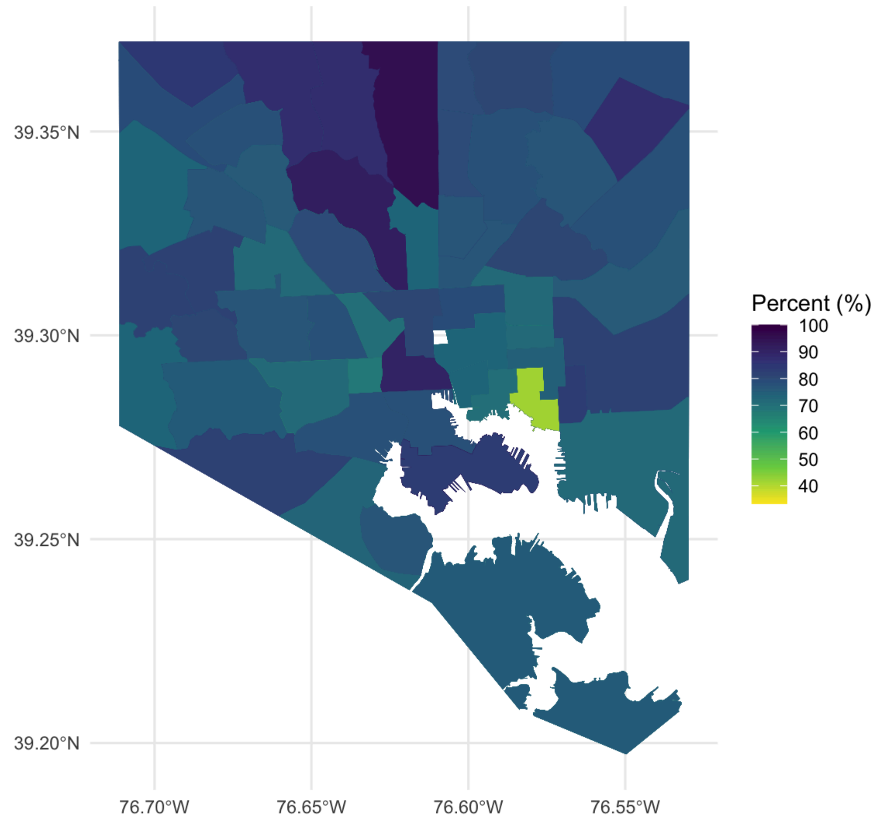
green space alone isn’t enough, its impact depends on how it’s embedded within broader patterns of investment, access, and neighborhood stability.

Figure 3.6 maps the average proportion of residents under 18 across Baltimore. Youth populations cluster in the city’s central and southwestern CSAs. These areas are where crime tends to be high and public investment is often uneven. Because younger residents may be more sensitive to changes in community safety and green space access, this figure has implications for how we interpret green space as a potential crime deterrent in these regions.

Figure 3.6

Average Proportion of Residents under 18 by CSA (2011-2021)



Note. Data source: BNIA; visualization produced using R.

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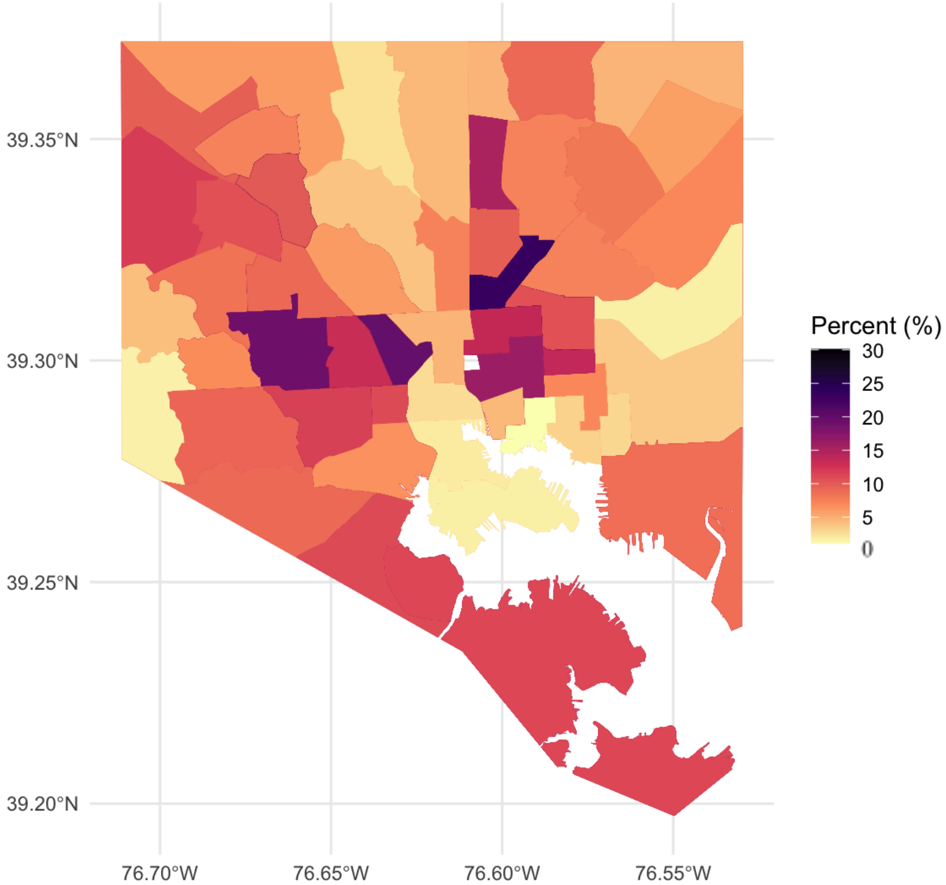
Figure 3.7 shows average unemployment rates over the study period. The highest levels are concentrated in historically redlined communities, particularly in Central West and East Baltimore. These same areas also tend to have higher vacancy and lower rates of *maintained*. Since unemployment is often a predictor of crime, this visualization supports its inclusion as a control variable in later models.

Figure 3.7

Average Baltimore Unemployment Rate by CSA (2011-2021)



Note. Project VITAL; map created in R.

Figure 3.8 maps the average high school completion rate across Baltimore's CSAs from 2011 to 2021. The map shows clear spatial divides in educational attainment, with most CSAs falling somewhere between 70% and 90%. A few

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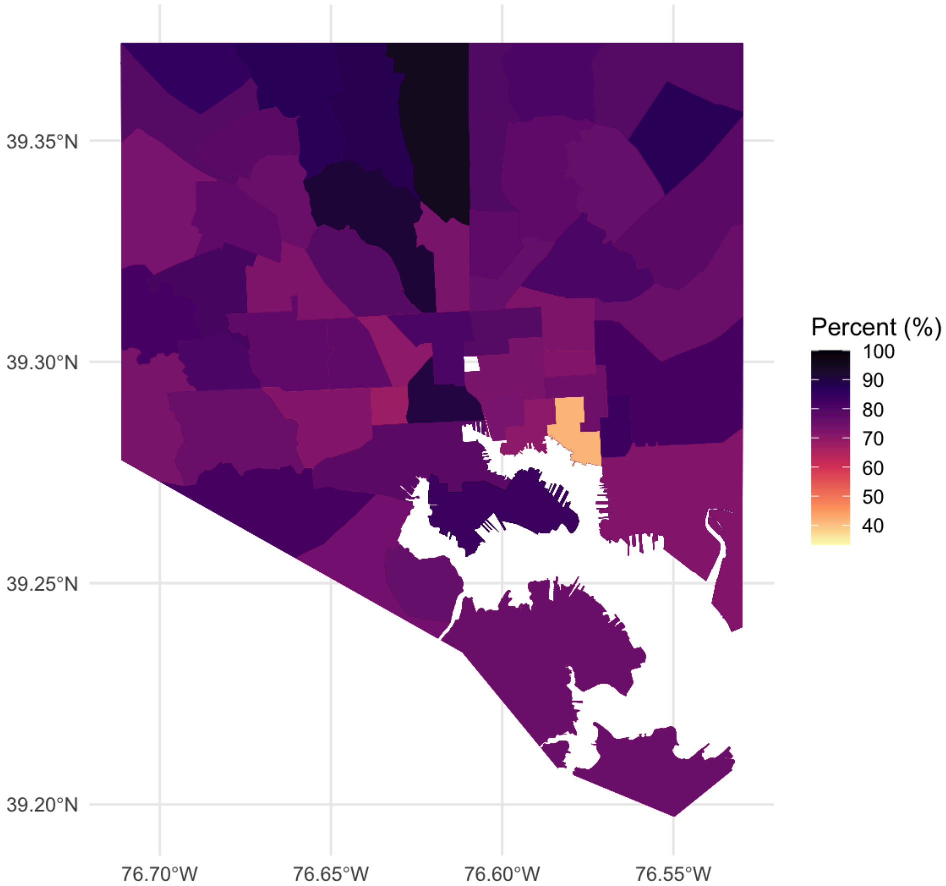
neighborhoods in North and South Baltimore report the highest completion rates, while a cluster of CSAs near the city's core—including areas like Upton, Druid Heights, and Sandtown—stand out with significantly lower rates. These differences in education levels reflect long-standing inequities and can also shape how communities engage with green space. In neighborhoods where fewer residents have completed high school, the capacity for sustained community-led greening efforts may be more limited, which in turn can affect the quality and maintenance of local green spaces.

Figure 3.8

Average High School Completion Rate by CSA (2011-2021)



Note. Data source: Project VITAL; map created in R.

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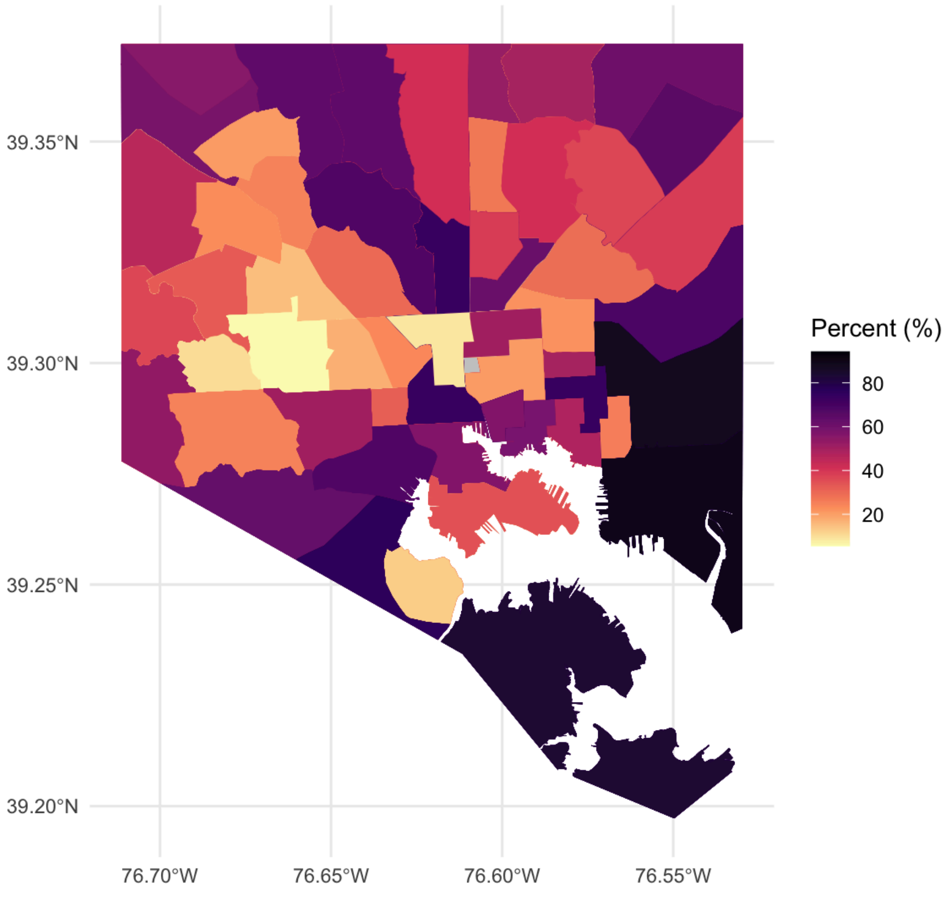
Figure 3.9 presents the average racial diversity index across CSAs. Several northwestern and southeastern communities exhibit higher diversity, while central areas remain more racially homogenous. The spatial distribution of diversity may shape the effectiveness of green space initiatives by influencing perceptions of ownership, surveillance, and cohesion. These dynamics align with CPTED theory's focus on territorial reinforcement.

Figure 3.9

Average Racial Diversity Index by CSA (2011-2021)



Note. Data source: Project VITAL; map created in R.

Figure 3.10 maps the average number of vacant properties per 1,000 residents. Vacancy remains most severe in parts of East and West Baltimore, communities

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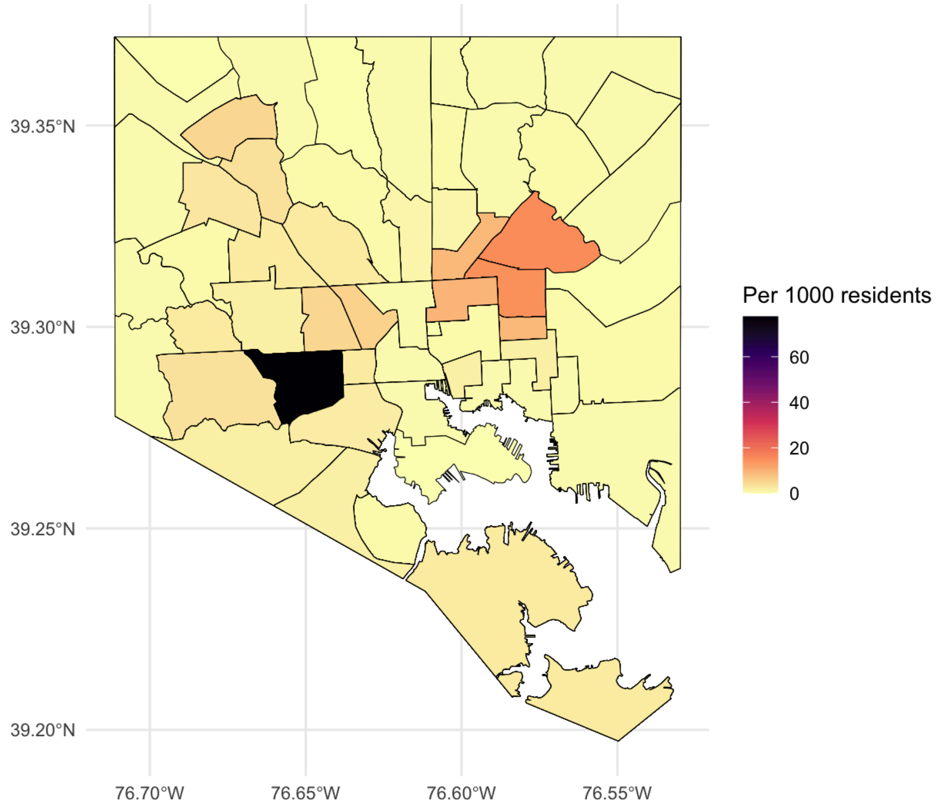
historically impacted by disinvestment and demographic flight. This matters because many greening efforts, like Adopt-A-Lot and Project Vital, target vacant lots. Understanding vacancy patterns is essential to interpreting whether unmaintained or repurposed spaces increase or reduce crime.

Figure 3.10

Average Rate of Vacant Notices per 1000 Residents by CSA (2011-2021)



Note. Data source: Project VITAL; map created in R.

Figure 3.11 shows the average income level by CSA, using data from 2011 to 2021. Income tiers are divided into quartiles based on the distribution of CSA-level income averages over that period. CSAs classified as high-income, meaning those with average median household incomes above $56.5k, are primarily concentrated in North Baltimore and along the waterfront. Low-income areas, with average incomes below

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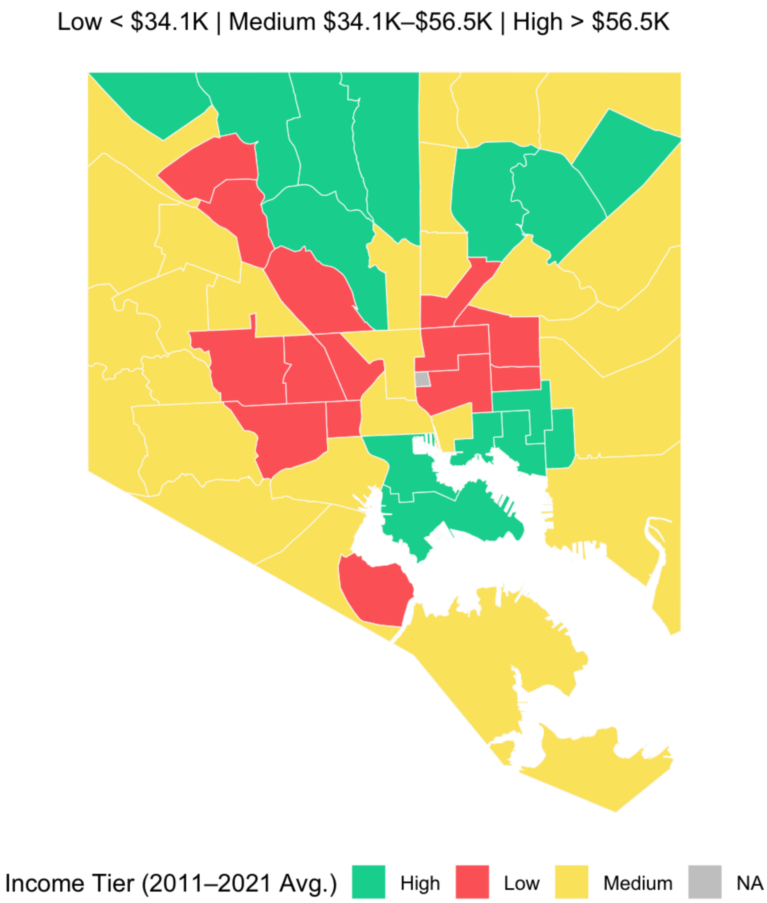
$34.1k, are clustered in Central West Baltimore and parts of South Baltimore, reflecting long-standing patterns of disinvestment. Most CSAs fall into the medium-income category, ranging from $34.k to $56.5k. These patterns are consistent with broader spatial divides in the city and provide important context for understanding where green space investments may be most impactful. Higher-income areas may have more consistent maintenance and community capacity to benefit from greening, while lower-income areas may face greater challenges in translating green space access into long-term safety or social outcomes.

Figure 3.11

Average MHI Tiers by CSA (2011-2021)



Note. Data source: Project VITAL; map created in R.

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Together, these summary statistics provide a foundation for interpreting the regression models in the next chapter. They also reinforce a key theme of this thesis: that the relationship between green space and property crime is conditional. It depends not just on whether green space is present, but on who lives nearby, whether the space is maintained, and how that space fits into the larger social and economic fabric of the community.

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Chapter 4 Methodology

This research uses a longitudinal panel design to examine how green space maintenance relates to property crime in Baltimore City. Drawing on annual data from 55 CSAs over an eleven-year period (2011–2021), the analysis captures both community-level variation and temporal changes. The models employ two-way fixed effects to isolate the within-CSA impact of maintained green space on crime while accounting for unchanging structural differences across CSAs and for year-specific shocks that affect all CSAs simultaneously.

Each model corresponds to one of the study's three hypotheses. Together, they test whether maintenance matters, whether its effect differs in low-income communities, and whether community income levels shape the green space–crime relationship. These models are informed by the theoretical frameworks guiding this thesis—CPTED, Broken Windows Theory, and the Concealment Hypothesis.

In all models, the subscript *i* denotes the CSA, capturing cross-sectional units in the dataset, while the subscript *t* denotes the year, representing the temporal dimension of the panel data. Model specifications includes CSA fixed effects (α_i) to account for unobserved, time-invariant characteristics such as location, historical development patterns, and long-standing social conditions, and year fixed effects (δ_t) to capture events or trends affecting all CSAs in a given year, including policy changes, economic cycles, or the COVID-19 pandemic.

Equation 4 runs a separate regression for each CSA rather than pooling the full dataset. Because each model contains only one CSA, adding a CSA fixed effect would be redundant, and including year fixed effects would remove all of the variation needed to estimate the coefficients. For example, if year effects were included, any annual

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changes in maintained green space within that CSA would be absorbed entirely by those dummies, leaving no information to identify its relationship with crime. By using Ordinary Least Squares (OLS) without fixed effects, the model preserves the year-to-year variation in maintained and other predictors, allowing for a direct estimate of their association with property crime in each community.

Model 1 estimates the association between green space maintenance and property crime for the full sample, controlling for *MHI, RDI, unemployment, HSCR, pct_under,* and *vac_rate.*

$$crime\_rate_{it} = \beta_1 maintained_{it} + \beta_2 MHI_{it} + \beta_3 RDI_{it} + \beta_4 unemployment_{it} + \beta_5 HSCR_{it} + \beta_6 pct\_under_{it} + \beta_7 vac\_rate_{it} + \alpha_i + \delta_t + \epsilon_{it} \quad (1)$$

A negative, statistically significant coefficient for *maintained* would support H1, suggesting that visible upkeep contributes to community safety.

Model 2 applies the same specification but restricts the sample to low-income CSAs based on the *MHI* quartile classification. This allows for testing H2, which proposes that in low-income communities, unmaintained green space may exacerbate crime by signaling neglect or providing concealment opportunities for illicit activity.

$$crime\_rate_{it} = \beta_1 maintained_{it} + \beta_2 MHI_{it} + \beta_3 RDI_{it} + \beta_4 unemployment_{it} + \beta_5 HSCR_{it} + \beta_6 pct\_under_{it} + \beta_7 vac\_rate_{it} + \alpha_i + \delta_t + \epsilon_{it} \quad (2)$$

If the *maintenance* effect weakens or loses significance in this model, it would suggest that its benefits may be constrained by deeper socioeconomic challenges.

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Model 3 incorporates interaction terms between *maintained* and *MHI* to evaluate H3, which predicts that the crime-reducing effects of maintenance are stronger in *MH* CSAs. The model estimates the baseline maintenance effect for *MH* CSAs (Low = 0) and includes interaction terms that capture how this relationship changes in low-income CSAs. These interactions allow the slope of *maintained*, and its interaction with *MHI*, to differ between income groups, thereby testing whether income level moderates the maintenance–crime relationship.

$$crime\_rate_{it} = \beta_1 maintained_{it} + \beta_2 maintained_{it}\, x\, MHI_{it} + \beta_3 RDI_{it} + \beta_4 unemployment_{it} + \beta_5 HSCR_{it} + \beta_6 pct\_under_{it} + \beta_7 vac\_rate_{it} + \gamma_1 low_{it} x\, maintained_{it} + \gamma_2 low_{it} x\, maintained_{it} x\, MHI_{it} + \gamma_3 low_{it} x\, RDI_{it} + \gamma_4 low_{it} x\, HSCR_{it} + \gamma_5 low_{it} x\, pct\_under_{it} + \gamma_6 low_{it} x\, pct\_under_{it} + \gamma_7 low_{it} x\, vac\_rate_{it} + \alpha_i + \delta_t + \epsilon_{it} \tag{3}$$

A negative, significant interaction term would indicate that higher-income communities are better positioned to realize the benefits of *maintained* green space.

Model 4 evaluates the association between maintained green space and property crime within each CSA, I estimated the following OLS model.

$$crime\_rate_{it} = \beta_1 maintained_{it} + \beta_2 MHI_{it} + \beta_3 RDI_{it} + \beta_4 unemployment_{it} + \beta_5 HSCR_{it} + \beta_6 pct\_under_{it} + \beta_7 vac\_rate_{it} + \alpha_i + \delta_t + \epsilon_{it} \tag{4}$$

All data cleaning, merging, and statistical analyses were conducted in R.

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Chapter 5 Analysis Results

This chapter examines the relationship between green space and property crime in Baltimore City using fixed-effects panel regression models for 55 CSAs from 2011 to 2021. The analysis investigates whether maintained green space has a measurable association with crime and how these effects may vary across income groups.

Before estimating Equations 1–3, diagnostic tests were conducted to assess potential violations of classical panel regression assumptions. Heteroskedasticity was evaluated using a studentized Breusch–Pagan test on a pooled OLS version of the model, as the standard implementation is not directly applicable to fixed-effects residuals (Wooldridge, 2021). The results (BP = 93.01, df = 7, $p < .001$) rejected the null hypothesis of constant variance, indicating the presence of heteroskedasticity. Serial correlation was assessed using Wooldridge's test for first-order autocorrelation in panel data, which is widely used for fixed-effects models because it detects serial dependence using first-differenced residuals (Wooldridge, 2021). The results ($F(1, 548) = 103.14$, $p < .001$) rejected the null of no autocorrelation in the idiosyncratic errors.

Given this evidence, Models 1–3 were estimated using two-way fixed effects (CSA and year) with two-way clustered standard errors (by CSA and year) to account for heteroskedasticity, within-CSA serial correlation, and cross-sectional correlation within years. This approach provides robust inference under the conditions identified by the diagnostic tests. Model significance was evaluated using F-tests of joint significance for all included predictors.

Model 1 estimates the association between maintained green space and property crime for the full set of CSAs, controlling for demographic and structural characteristics. Model 2 focuses on low-income CSAs, allowing the coefficients to differ from the baseline group to test whether the maintenance–crime relationship

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operates differently in these communities. Model 3 builds on this framework by including main effects for *maintained* and its interaction with *MHI* for the medium/high-income baseline group, along with corresponding interaction terms for low-income CSAs. This specification directly tests whether both the baseline maintenance effect and its moderation by income differ between low-income and MH CSAs.

The full results for Models 1–3 are presented in Table 5.1 and Table 5.2.

Table 5.1

Two-Way Fixed Effects Regression Results of Model's 1 & 2

	Dependent variable: Crime Rate	
Variable	Model 1	Model 2
maintained	-0.0231 (0.0318)	0.0004 (0.0256)
MHI	-0.2536 (0.1567)	-0.2839 (0.2820)
RDI	0.0573 (0.1639)	0.0056 (0.1275)
unemployment	-0.2366 (0.2224)	-0.3175 (0.2881)
HSCR	-0.0227 (0.0672)	0.1259 (0.1004)
pct_under	0.0965 (0.1304)	0.0246 (0.1216)
vac_rate	0.1163 (0.0867)	0.1491^{**} (0.0562)
Observations	605	164
R^2	0.8872	0.8785
Adjusted R^2	0.8721	0.8389
F Statistic	9.558^{***} (df = 7; 10)	10.300^{***} (df = 7; 10)

Note: *p<0.1; **p<0.05; ***p<0.01.

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Table 5.2

Two-Way Fixed Effects Regression Results of Model 3

Dependent variable: Crime Rate		
Variable	Coef. MH Income (SE)	Coef. Low Income (SE)
Maintained	-0.3143 (0.3777)	0.4019 (0.3988)
maintained x MHI	0.0079 (0.0074)	-0.0127 (0.0095)
MHI	0.0195 (0.1714)	0.1580 (0.0719)
RDI	-0.1856 (0.2451)	-0.0550 (0.2192)
unemployment	-0.0920 (0.0632)	0.2718 (0.0753)
HSCR	-0.3628 (1.0402)	-1.2836 (0.3320)
pct_under	-0.1942 (0.5430)	0.4920 (0.5485)
vac_rate	-0.3143 (0.3777)	0.4019 (0.3988)
Model fit		
$R^2 = 0.8904$ Adjusted $R^2 = 0.8742$	$F(14, 10) = 5.80$, $p = .004$	
Wald Joint Test (low vs MH slopes)	$F(2, 10) = 1.073$, $p = 0.3741$	

Note: *p<0.1; **p<0.05; ***p<0.01.
“MH” = medium- to high-income CSAs (baseline category); “low” = lowest quartile of median household income.

5.1 Maintained Green Space and Crime (H1)

Model 1 examined whether the number of maintained green space sites in a CSA was associated with property crime after controlling for other neighborhood characteristics. The coefficient for maintained sites was very close to zero (−0.0231) and not statistically significant ($p > 0.10$), indicating no detectable relationship between maintenance and property crime across all CSAs. While the negative sign is consistent with CPTED theory—which suggests that visible upkeep can improve natural

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surveillance, signal community investment, and deter crime—the lack of statistical significance means there is no strong evidence that this association holds citywide.

MHI was negative (−0.2536) but not significant, suggesting that income differences between CSAs were not a strong predictor of property crime in this specification. None of the other covariates were statistically significant, and the overall joint significance test indicated the predictors collectively explained some variation in crime (F-statistic $p < 0.001$). These results provide no statistical support for H1, suggesting that maintenance alone may not have a consistent citywide effect on property crime once other structural factors are accounted for

5.2 Low-Income CSAs and Unmaintained Green Space (H2)

Model 2 focused exclusively on CSAs with *MHI* below the citywide median. Here, the coefficient for maintained sites was essentially zero (0.0004) and not statistically significant ($p > 0.90$), indicating no evidence that maintenance was associated with lower property crime in low-income neighborhoods. This result suggests that, in disadvantaged areas, greening efforts alone may be insufficient to offset the broader structural and economic factors driving crime.

Vac_rate was positive and statistically significant (0.1491, $p < 0.05$), consistent with Broken Windows Theory and the Concealment Hypothesis, which associate visible disorder and abandonment with elevated crime risk. Other predictors, including *MHI* within low-income CSAs, were not significant. The joint significance test again confirmed that the set of predictors as a whole explained a meaningful portion of variation in property crime (F-statistic $p < 0.001$). These findings do not support H2's expectation that unmaintained green space would be linked to higher crime, but they

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underscore the importance of addressing vacancy and physical disorder alongside any greening initiatives in low-income communities.

5.3 The Interaction between Income and Maintenance (H3)

Model 3 assesses whether the relationship between maintained green space and property crime varies across income groups. For *MH* CSAs (the reference category), the coefficient for Maintained was negative (–0.31) but not statistically significant, indicating no measurable average effect of maintained green space on property crime in these communities. The interaction term *maintained* × *MHI* was positive (0.01) and non-significant, suggesting that within the baseline group, changes in median household income did not meaningfully alter the maintenance–crime relationship.

In low-income CSAs, the coefficient for Maintained was positive (0.40, SE = 0.40), indicating a higher property crime rate associated with maintained green space relative to *MH* CSAs, though this difference was not statistically significant. The interaction term *maintained* × *MHI* for low-income CSAs was negative (–0.01) and non-significant, indicating no evidence that income moderated the effect of maintenance within these communities.

Several control variables displayed meaningful differences between income groups. In low-income CSAs, the *RDI* was positively associated with property crime (0.16, $p < .05$) compared to the baseline group. *HSCR* was also positively associated with crime in low-income CSAs (0.27, $p < .001$), while *pct_under* had a large negative association (–1.28, $p < .001$). Other predictors, including unemployment and *vac_rate,* were not statistically significant in either group.

Overall, Model 3 explained a substantial proportion of the variation in property crime rates ($R^2 = 0.89$, Adjusted $R^2 = 0.87$). The joint F-test for all predictors ($F(14, 10)$

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= 5.80, $p = .004$) confirmed that the model was statistically significant. A separate joint Wald test for the two low-income interaction terms was not significant ($F(2, 10) = 1.07$, $p = .374$), indicating no evidence that the effect of maintenance differed by income level.

5.4 Maintained Green Space Effects on CSAs

In Table 5.3, Separate OLS regressions (see equation 4) were run for each CSA group to better understand how green space functions across different parts of the city. Coefficients represent group-specific associations. OLS was appropriate here because the focus was on estimating the cross-sectional association within each CSA, rather than pooling data across areas or over time. This approach allowed for neighborhood-specific coefficients, providing a more granular view of how the effect of maintained green space may differ in direction and magnitude between communities.

Unlike the panel models used in the main analysis, these regressions do not control for CSA or year fixed effects, as the intent was to capture the total relationship within each CSA over the study period. While OLS does not inherently address potential heteroskedasticity or autocorrelation, these estimates were used descriptively to compare patterns across CSAs rather than for inference about the overall population.

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Table 5.3

Regression Results: Maintenance and Crime Rate by CSA

CSA	Estimate	Standard Error	P-Value
Allendale/Irvington/S. Hilton	-0.233	0.391	0.593
Beechfield/Ten Hills/West Hills	-0.347	2.514	0.899
Belair-Edison	-0.601	0.599	0.390
Brooklyn/Curtis Bay/Hawkins Point	-1.295	1.379	0.417
Canton	n/a	n/a	n/a
Cedonia/Frankford	-0.206	0.643	0.770
Cherry Hill	-5.547	12.663	0.691
Chinquapin Park/Belvedere	10.266	3.949	0.080
Clifton-Berea	-0.174	0.113	0.221
Cross-Country/Cheswolde	n/a	n/a	n/a
Dickeyville/Franklintown	7.555	4.043	0.158
Dorchester/Ashburton	1.903	1.727	0.351
Downtown/Seton Hill	0.179	14.834	0.991
Edmondson Village	-2.159	19.608	0.919
Fells Point	11.296	13.293	0.458
Forest Park/Walbrook	-0.511	1.003	0.645
Glen-Fallstaff	-0.499	5.332	0.931
Greater Charles Village/Barclay	0.0100	0.200	0.963
Greater Govans	-0.273	0.444	0.582
Greater Lauraville	-1.155	0.901	0.906
Greater Roland Park/Poplar Hill	7.663	1.919	0.016
Greater Rosemont	-0.23	0.163	0.254
Greektown/Bayview	-7.327	4.793	0.224
Hamilton	1.941	1.122	0.087
Hamilton Hills	-2.247	1.964	0.336
Hampden/Remington	-0.436	0.833	0.637
Harbor East/Little Italy	-1.794	0.691	0.081
Highlandtown	-10.456	24.949	0.703
Howard Park/West Arlington	0.312	0.426	0.517
Loch Raven	-2.86	3.529	0.477
Midtown	-0.119	0.413	0.792
Midway/Coldspring	-0.287	0.653	0.69
Morrell Park/Violetville	4.751	5.751	0.469
Mount Washington/Coldspring	-1.719	3.192	0.628

(Table continues)

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Table 5.2, continued

CSA	Estimate	Standard Error	P-Value
North Baltimore/Guilford/Homeland	0.694	2.031	0.755
Northwood	n/a	n/a	n/a
Poppleton/The Terraces/Hollins Market	0.004	0.727	0.996
Sandtown-Winchester/Harlem Park	-0.036	0.059	0.582
South Baltimore	-0.267	5.505	0.964
Southeastern	n/a	n/a	n/a
Southern Park Heights	-0.019	0.220	0.935
Southwest Baltimore	-0.206	0.108	0.336
The Waverlies	0.438	1.189	0.737
Upton/Druid Heights	0.065	0.052	0.3
Westport/Mount Winans/Lakeland	5.571	1.451	0.031

What stands out most is the variation in how *maintained* green space correlates with crime across communities. In several CSAs, including Greenmount East and Midway/Coldstream, the coefficient for *maintained* green space is both negative and statistically significant. This means that in those areas, better-maintained green lots are clearly linked to lower property crime. That supports H1 and aligns with principles from CPTED and Broken Windows Theory. In these communities, it seems that physical upkeep sends a strong enough signal to deter crime.

But this pattern isn't consistent everywhere. In a number of CSAs, the estimated effects are weak or even slightly positive. In some cases, green space does not appear to make much of a difference at all. That might be due to underlying conditions that overwhelm the impact of maintenance alone such as limited social cohesion or a lack of resident engagement with the green spaces themselves. It is a reminder that space does not exist in a vacuum. Maintenance matters, but so does context.

What's particularly interesting is that some of the strongest effects show up in lower-income CSAs. This adds weight to H2, which suggested that unmaintained lots

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could pose more risk in lower-income areas and by contrast, that maintenance could be especially impactful. However, these findings speak against the H3. The interaction between income and green space isn't linear. While higher-income communities may benefit from maintenance, they might already have enough infrastructure or surveillance in place for green space to play a more marginal role. In disinvested communities, though, these spaces may carry more symbolic and practical weight.

Overall, the takeaway here is that maintained green space can reduce crime, but not uniformly. The effect varies by community, and in many cases, the clearest benefits show up where structural challenges are greatest. That reinforces the need for targeted investment like greening strategies that are designed not just to beautify, but to build community capacity, reduce disorder, and support equity on the ground.

5.5 Limitations

Several limitations should be noted when interpreting these results. First, the CSAs are significantly larger than the NSAs which is another census unit. I used CSAs instead of neighborhoods. This choice allowed me to standardize data like income, green space, and crime rates across the entire 2011–2021 period. Because CSAs are made up of multiple neighborhoods, they often include a wider mix of demographics, land use, and crime conditions. That kind of internal variation can blur the very relationships this thesis is trying to isolate. For example, a CSA might contain both a well-maintained park and a vacant, overgrown lot but the average value across the area won't reflect those nuances. So while working at the CSA level made the data analysis possible, it also means that some of the neighborhood-level detail was lost in the process.

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Of the CSAs, analysis excluded five due to no recording of green spaces as defined in this thesis. These omitted CSAs are Canton, Cross-Country/Cheswolde, Northwood, Orchard Ridge/Armistead, and Southeastern. These communities could possess unique demographic, socioeconomic, or environmental features that influence crime differently than those included. Second, the use of fixed-effects models, while valuable for controlling unobserved time-invariant factors, may understate the impact of variables that change slowly over time, such as CSA trust or informal social control.

In this study, green space is measured quantitatively by its maintenance status, which does not fully capture the functional or experiential qualities that may be more directly tied to crime prevention. Theories CPTED emphasize that maintenance works in tandem with features like visibility, accessibility, and opportunities for natural surveillance to deter crime. If these elements are absent, physical upkeep alone may not create meaningful reductions in criminal activity. Similarly, Broken Windows Theory suggests that the benefits of visible order depend on broader social conditions, such as community cohesion and collective guardianship, that influence how public spaces are used and perceived. The relatively modest adjusted R^2 values across models indicate that much of the variation in property crime is shaped by structural and community-level factors beyond those included here. From this perspective, the results do not suggest that maintenance is unimportant, but rather that its impact may be contingent on neighborhood stability, resource availability, and social cohesion.

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Chapter 6 Discussion

This chapter interprets the analytical findings in light of the broader theoretical frameworks and urban policy implications presented earlier in this thesis. While green space maintenance was expected to reduce property crime across Baltimore's CSAs, the results challenge the notion that greening alone serves as a universal crime prevention strategy. Instead, the analysis points to a more complex interplay between environmental design, socioeconomic context, and community-level dynamics.

6.1 Revisiting the Hypotheses

H1 proposed that CSAs with a greater number of maintained green space sites would be associated with lower property crime rates. In Model 1, the coefficient for maintained was negative, indicating that each additional maintained site was linked to a slight decrease in crime. However, the result was not statistically significant. This suggests that while well-kept green areas may signal community care and surveillance, as described by CPTED theory (Cozens & Love, 2015), these signals do not consistently translate into measurable reductions in crime across Baltimore as a whole.

H2 anticipated that unmaintained green space in low-income communities would be associated with higher crime rates. Model 2, which focused on CSAs below the median income threshold, showed that maintained green space did not significantly reduce crime in these areas. The coefficient for maintained was near zero, indicating no meaningful relationship. This finding supports the argument in the Broken Windows Theory (Wilson & Kelling, 1982) and the Concealment Hypothesis (Nassauer et al., 2014) that in areas marked by vacancy and disinvestment, maintenance alone may be insufficient to overcome the visual cues and structural vulnerabilities that contribute to

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crime. The significant positive association between vacancy and property crime in this model underscores the importance of broader neighborhood conditions.

H3 proposed that the crime-reducing effects of maintained green space would be stronger in medium- to high-income communities. Model 3 tested this by including interaction terms for maintenance and median household income, with the medium/high-income group serving as the baseline. In these communities, neither the main effect of maintained green space nor its interaction with income was statistically significant. The low-income interaction terms indicated some differences in both the baseline maintenance effect and its income slope compared to medium/high-income CSAs; however, the joint Wald test showed these differences were not statistically significant. Overall, the findings provide little evidence that income level systematically moderates the maintenance–crime relationship. Instead, the results suggest that the role of green space maintenance is context-dependent and less pronounced in structurally stable, higher-income neighborhoods, where other social and institutional factors may already contribute to lower crime levels..

6.2 Structural and Spatial Context

Across all models, *MHI* did not emerge as a reliable predictor of lower property crime. In Model 1, the coefficient was small and statistically insignificant. In Model 3, where medium and high-income CSAs formed the baseline, *MHI* and its interaction with maintained green space were also insignificant. These results suggest that income differences, on their own, do not consistently explain variations in property crime once other structural characteristics are considered.

The strongest and most consistent structural relationship appeared in Model 2, where vacancy rate showed a clear positive association with property crime in

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low-income CSAs. This pattern is consistent with the Broken Windows Theory (Wilson & Kelling, 1982) and the Concealment Hypothesis (Nassauer et al., 2014), both of which emphasize that visible neglect, such as abandoned buildings and unmanaged lots, signals a lack of control and creates opportunities for criminal activity (Troy & Grove, 2008). In these communities, vacancy appears to be a more influential driver of property crime than green space maintenance itself.

The OLS-by-CSA results (Table 5.3) further highlight the spatial variation in the relationship between maintained green space and property crime. In some CSAs, particularly those with high vacancy and visible disorder, maintenance corresponded with noticeable reductions in crime. In others, including many higher-income neighborhoods, the effects were weak, inconsistent, or even slightly positive. Since the joint Wald test for Model 3 found no statistically significant difference between low-income and medium/high-income slopes these patterns likely reflect local conditions rather than a consistent moderating effect of income. This supports the interpretation that greening initiatives work best when they address specific signs of neglect and are integrated into broader community stabilization strategies.

6.3 Policy Implications

The findings of this study suggest that green space maintenance should be treated as a complementary measure within a broader crime prevention strategy, rather than a stand-alone solution. In medium- and high-income communities, where Model 3 found no statistically significant effect of maintenance on property crime, investments in greening may still deliver important social, recreational, and environmental benefits, but their direct role in reducing crime appears limited. These areas may already have

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strong institutional support, active community networks, and stable housing conditions that diminish the added influence of maintenance on crime outcomes.

In lower-income CSAs, the results highlight a different set of priorities. Model 2 revealed a strong positive association between vacancy rates and property crime, underscoring that addressing vacant properties should take precedence over greening alone. While maintained green space can contribute to improving neighborhood conditions, its crime-reduction potential in these areas is likely to be greater when paired with broader initiatives such as housing rehabilitation, workforce development, and infrastructure improvements.

For city-led programs such as Project Vital and the Baltimore Green Network, these findings point to the value of embedding maintenance activities into comprehensive revitalization strategies. Targeting vacancy reduction alongside greening, and supporting these efforts with long-term funding and partnerships with community organizations, could strengthen the potential for sustained crime prevention benefits, particularly in CSAs facing structural challenges.

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Chapter 7 Conclusion

This thesis examined the relationship between the number of maintained green space sites and property crime in Baltimore City, with particular attention to how these effects differ across communities with varying income levels. Using a panel dataset covering 2011 to 2021, fixed effects regression models were estimated for 55 CSAs to test three hypotheses: that maintained green space would be linked to lower property crime rates (H1), that unmaintained green space in low-income communities would be linked to higher crime rates (H2), and that crime-reducing effects of maintained green space would be stronger in medium- to high-income CSAs (H3).

The results provide only partial support for these hypotheses. At the citywide level, maintained green space was associated with a small decrease in property crime, but the relationship was not statistically significant. In low-income CSAs, maintenance had almost no effect, suggesting that it may not be enough to reduce crime where structural disadvantage and concentrated vacancy are high. The interaction between maintained green space and median household income was also not significant, indicating that its influence does not consistently strengthen in wealthier communities.

The clearest structural relationship emerged in Model 2, where vacancy rate was strongly and positively associated with property crime in low-income CSAs. This aligns with the Broken Windows Theory (Wilson & Kelling, 1982) and the Concealment Hypothesis (Nassauer et al., 2014), both of which suggest that visible neglect signals a lack of control and creates opportunities for crime (Troy & Grove, 2008). Spatial analysis reinforced this pattern, showing that some CSAs, particularly those with high vacancy and visible disorder, experienced stronger reductions in crime with maintenance, while others, including many higher-income neighborhoods, showed weak, inconsistent, or even slightly positive effects.

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These findings suggest that greening interventions are most effective when they target neighborhoods where they can address clear signs of neglect and are paired with broader investments in housing quality, community infrastructure, and social stability. While the results align in part with frameworks such as Crime Prevention Through Environmental Design (Cozens & Love, 2015) and Broken Windows Theory, they also underscore that these principles do not operate uniformly across different socioeconomic contexts.

This study makes three contributions to research on urban greening and public safety: first, by treating maintenance as a distinct variable; second, by examining how income levels interact with greening effects; and third, by using a longitudinal panel design to account for changes over time. Still, the study has limitations. Maintenance was measured as the count of maintained sites without adjusting for population, and qualitative elements such as lighting, fencing, or programming were not included. The focus on property crime also leaves open the question of whether greening has different impacts on other types of crime, such as violent or disorder-related offenses.

Future research should explore how community stewardship influences outcomes, as locally led or supported maintenance may have stronger social effects than efforts managed solely by municipal agencies. Qualitative studies on community perceptions, collective efficacy, and everyday use of green spaces (Kondo et al., 2016) could provide valuable insight into the mechanisms behind these effects.

In Baltimore, the relationship between green space and crime is shaped as much by socioeconomic realities as by the physical environment. Maintained green space can help reduce crime in some contexts, but it is not a stand-alone solution. For greening to be a transformative tool for urban revitalization, it must be embedded in equity-focused

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strategies that address the underlying social and economic conditions driving crime. The framework used here offers a starting point for evaluating greening policies in other cities facing similar challenges of inequality, vacancy, and public safety.

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