## THE UNIVERSITY OF CHICAGO

# How Crime Relates to Investment and Disinvestment in Residential Properties: A Baltimore City Case Study

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## Abstract

Urban communities suffer from a spiral of decay where poor conditions—structural and social induce crime, and crime worsens those conditions. Policies attempt to aid these blighted areas through crime prevention; however, the literature overlooks how residents, municipalities, and communities invest and disinvest in homes and neighborhoods in relation to surrounding crime. This study uses panel data on crime and housing indicators from the Baltimore Police Department and the Baltimore Department of Housing and Community Development to model the relationship between crime and residential investment in communities within Baltimore City, Maryland, from 2015 to 2021. Contrary to the expected narrative, the study finds a significant increase in rehabilitation projects within higher crime areas, suggesting unexpected patterns of investment. However, these areas also see fewer demolitions and maintain a higher proportion of unoccupied homes, suggesting that investment and disinvestment can coexist. Thus, Baltimore may consider supplemental housing investment in high crime areas.

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#### 1. Introduction

Crime is one of the main determinants of neighborhood appeal. Typically, if the crime rate increases in a certain area, the value of nearby homes will drop (Ceccato & Wilhelmsson, 2011, 2012; Clark & Cosgrove, 1990; Ihlanfeldt and Mayock, 2010). But beyond shaping its surrounding environment, crime also responds to it. For example, resident reports of "collective efficacy" and a higher sense of community are associated with lower rates of crime and greater perceptions of safety (Sampson et al., 1997; Cancino, 2005; Cantora et al., 2016; Iyer et al., 2020). Conversely, tangible signs of disorder are associated with higher perceptions and rates of crime (Wilson & Kelling, 1982; Skogan, 1992; Sampson et al., 1997; Cantora et al., 2016).

Accordingly, areas that suffer from high rates of crime find themselves stuck in a spiral: crime begets disorder and decay; disorder and decay beget crime (Skogan, 1992). Much of the literature seeks to quantify the effects of these endogenous determinants of crime on realized crime rates, offering insight into why certain communities remain in this spiral. However, there is less focus on how crime relates to a potential avenue out of decay: investment in residential properties and neighborhoods. Thus, I am interested in whether this type of investment in Baltimore—a city notorious for high rates of crime and a debilitating amount of vacant<sup>1</sup> residential properties—is at all responsive to crime rates. The answer to this question may help inform the evaluation of policies that aim to target both crime and housing instability, and whether those policies will deliver on their promises. For example, if residential investment is not responsive to crime, then policymakers should be careful not to assume that crime prevention policies will have significant effects on moving communities out of blight<sup>2</sup>, given that a lack of

<sup>&</sup>lt;sup>1</sup> Baltimore uses "vacant and abandoned" to refer to buildings which are "uninhabitable" or no longer fit to house a resident (*Vital Signs 21, n.d.*).

<sup>&</sup>lt;sup>2</sup> Schilling & Pinzón (2008) use blight to describe "land so damaged or neglected that it is incapable of being beneficial to a community without outside intervention." In Baltimore, then, blight shows up as the preponderance of vacant and abandoned houses and lots that have long been detrimental and dangerous for the city's residents (Scott, 2020; Miller & Little, 2022; Thompson et al., 2023), and which is often credited with contributing

investment may remain. Accordingly, my research question is as follows: How does crime relate to investment and disinvestment in residential properties? Based on the literature, I hypothesize that areas with higher crime will see lower rates of investment; furthermore, areas with higher crime will see higher rates of disinvestment.

To model the relationship between crime and residential property investment and disinvestment, I focus on three arms of investment: individual investment through the rehabilitation of properties, municipal investment through the demolition of old properties, and community disinvestment through the share of unoccupied<sup>3</sup> homes. I investigate the relationship these measures have with total crime, as well as the breakdown of total crime into violent crime and property crime. I use panel data from 2015 to 2021, collected at the Community Statistical Area (CSA) level (Appendix A), in an OLS regression with two-way fixed effects that control for variation across years and CSAs. I also employ additional controls for race, ethnicity, age, education, employment, and poverty status. To describe the data, I use quantile classification methods to create choropleth maps of each variable used in the OLS model that visually depict changes in each variable over time (years) and space (CSAs) (figures 4-8 and Appendix F). In addition, I conduct a series of robustness checks to test the model under alternative specifications, such as varying the crime lags, replacing education attainment with median household income, and adding a COVID-19 dummy for years 2020-2021.

When looking at the relationship between crime and property rehabilitation permits, I find that as crime increases, rehabilitation permits also increase. This is a surprising finding which suggests that residents of areas with high crime may be interested in preventing their

to crime (Pappoe, 2016; Iyer et al., 2020; Thompson et al., 2023). Thus, I use the term "blight" in this paper to refer to conditions of physical disrepair that may be conducive to crime.

<sup>&</sup>lt;sup>3</sup> "Unoccupied" homes refer to those which are structurally sound and habitable, but lack a resident (*Vital Signs 21*, n.d.).

property from decaying. However, I also find that demolitions decrease, on average, in areas with higher crime, suggesting that dilapidated buildings still plague these areas, which may be contributing to more disorder and crime at the same time that residents are attempting to rehabilitate their properties. Finally, I find that in areas with higher crime, there are more unoccupied homes on average, signaling more community disinvestment.<sup>4</sup> This suggests that there may be opposite trends co-existing in Baltimore: even though individual residents are investing in their own properties in higher-crime areas, there is a deficiency of local government and community investment in these areas. Robustness checks (in Appendix E) affirm the significance of these findings, and I discuss the implications of these trends.

This paper proceeds as follows: in the next section (2), I introduce the situation in Baltimore, a city characterized by its high crime rate and its preponderance of vacant and abandoned homes. In Section 3, I discuss the relevant literature on the mechanisms driving crime, avenues for reducing that crime, and the effect of crime on home values. In Section 4, I introduce the data source for my model before moving to the discussion of the methods I use in Section 5. I present my findings and corresponding discussions in Section 6, along with a discussion of my model's limitations. I conclude in Section 7 with the implications of my findings for the evaluation of present-day policies in Baltimore that seek to address crime and the vacancy crisis.

<sup>&</sup>lt;sup>4</sup> Throughout the paper, "more community disinvestment" will convey the same meaning as "less community investment."

## 2. Background

## 2.1. Baltimore: A Vacant City Filled with Crime

Baltimore stands out among East Coast cities for a rather grim reason—despite the population boom in other cities, Baltimore is shrinking (Miller & Little, 2022). A long history of redlining in Baltimore established a pattern of displacement for black families and disinvestment in their communities (Pappoe, 2016). Meanwhile, white families were fleeing cities for the alluring suburbs, leaving many houses vacant in their wake (Cohen, 2001; Miller & Little, 2022). This was a common trend for cities in the rust-belt—such as Detroit, Pittsburgh, Buffalo, and Cleveland—and Baltimore was no exception. Experiencing a loss in manufacturing jobs, and with the suburbs not far, these cities, including Baltimore, witnessed their populations dramatically drop, allowing housing vacancies to skyrocket. Specifically in Baltimore, the population declined by 34.6% between 1950 and 2012 (Whiteman, 2014).

Baltimore is still struggling with a unique set of challenges as it deals with its high rates of vacancy and housing insecurity.<sup>5</sup> Some tools it has to address these challenges—such as eminent domain,<sup>6</sup> tax sale,<sup>7</sup> and receivership<sup>8</sup>— are often inadequate to address the scale of the city's problem (Miller & Little, 2022). As observed by Miller and Little, this deficiency perpetuates a vicious cycle wherein "the worst homes get worse, the same neighborhoods grow or decline, and the vacancy rates stay mostly stagnant" (ibid). Furthermore, these vacancies pose

<sup>&</sup>lt;sup>5</sup> Housing insecurity is a complex issue including multiple dimensions, such as being forced to move, consistently being unable to afford housing, or living in poor-quality housing conditions (Solari, 2024). Nneka Nnamdi of Fight Blight, a Baltimore-based campaign focused on creating safe communities, characterizes the problem in Baltimore: "Sixty percent of folks in Baltimore are housing insecure, which means people paid more than 30 percent of their income in housing costs" (McQueen, 2023).

<sup>&</sup>lt;sup>6</sup> Eminent domain refers to the government's power to acquire property for public use (Yu, 2015).

<sup>&</sup>lt;sup>7</sup> Tax sale is the practice whereby tax lien certificates are sold in a public auction by municipal tax collectors to generate funds owed by delinquent taxpayers (Pellegrino & Allocca, 1996; *Tax Sale Information*, n.d.).

<sup>&</sup>lt;sup>8</sup> Receivership is a mechanism whereby a receiver—either public or private—is appointed as a responsible caretaker of a deteriorated property (Listokin et al., 1984).

physical dangers to residents. In 2016, Baltimore resident Thomas Lemmon was killed when the wall of an abandoned building collapsed, burying him and his Cadillac (Scott, 2020).

Beyond issues with housing, Baltimore struggles with endemic crime. In 2004, Baltimore's homicide rate was three times the rate in Los Angeles, and five times that of New York. The city was even the inspiration for an NBC police drama, "Homicide: Life on the Street" (Collins, 2007, p. 421). These conditions are better understood in relation to the history of discriminatory practices that kept people—blacks, specifically—from access to wealth-building opportunities such as homeownership. In such circumstances, residents may need to turn to an informal economy—crime—in order to subsist (Pappoe, 2016, p. 131). It should not be a surprise, then, that this city—one which has experienced such disinvestment via segregationist policies—would presently struggle with some of the most notable rates of crime in the nation (Dao, 2005).

At the heart of this problem lies the irony of urban inequality—that those populations most in need of revitalization and reinvestment find themselves continuously disenfranchised by policies and practices. As Badger (2015) observes about Baltimore in particular, it is "active decisions and government policies that have undermined the same people and sapped them of their ability to rebuild, that have again and again dismantled the same communities, each time making them socially, economically, and politically weaker." I argue, then, that studying how these communities respond to the very circumstances these policies have forced upon them—ones of blight and high crime—may provide a new path to reduce this urban inequality.

#### 2.2. Looking at Mechanisms to Induce Investment

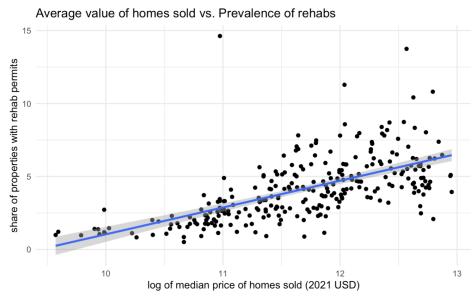
Baltimore has long wrestled with ways to reduce its housing blight, most of which involve direct investment in infrastructure—redeveloping properties and demolishing dilapidated ones, while physically marking the abandoned buildings that pose a threat to safety (Thompson et al., 2023). On their own, though, the city's efforts are often slow-moving and cannot fully address the community's needs, or solve the dangerous conditions in a timely manner (Miller & Little, 2022). This creates room for an inquiry— what else might induce housing investments, and provide a way out of this blight?

The urgency of this problem is exacerbated considering the positive relationship between physical disorder (such as collections of abandoned properties) and crime (Newman, 1972; Newman & Franck, 1982; Wilson and Kelling, 1982). Though Baltimore has seen a slight decrease in crime since 2015 (Appendices F.1, F.2, F.3), it is far from a resolved issue in the city. Moreover, although the city has extensive programs and plans for addressing crime, as well as addressing vacancies, there have not been impactful policies that acknowledge the interplay of these two issues.

Baltimore leaders are very aware of their housing and crime problems (even if they design policies that tackle them separately). To monitor these issues, the Baltimore Neighborhood Indicators Alliance (BNIA) publishes data on various "vital signs" to help the community measure progress toward meaningful outcomes at the community level (*Vital Signs 21*, n.d.). To make use of the plethora of US Census Department household and housing characteristic data at the census tract level, BNIA takes the 270 neighborhoods and converts them into 55 Community Statistical Areas (CSA), which are aggregated census tracts. (Appendix A, figure A.1, and Appendix B, figure B.1).

Among other categories, these vital signs provide valuable data on measures of housing-related blight, such as the percentage of properties that are vacant and abandoned, and the percentage of properties with tax liens that have been sold. There are also indicators for what I argue to be measures of the level of investment in these residential properties. Below, I introduce three of these indicators— the share of all properties with rehabilitation permits (figure 1), the rate of demolition permits (figure 2), and the share of unoccupied homes<sup>9</sup> (figure 3)— in relation to the value of homes sold.<sup>10</sup> The value of homes sold (represented as log of the median price of homes sold and plotted on the horizontal axis for all figures) may be understood as the return on investment for purchasing a home in that area.

Figure 1. Rehabilitation projects are more prevalent in neighborhoods with more expensive homes.



Source: Author's calculations using pooled data from First American Real Estate Solutions (FARES) and Baltimore Department of Housing and Community Development from 2015-2019. Calculations for adjusting prices to 2021 dollars can be found in Appendix C.3.

<sup>&</sup>lt;sup>9</sup> There is an important difference between "vacant and abandoned" homes and "unoccupied" homes. Whereas Baltimore uses "vacant and abandoned" to refer to buildings which are "uninhabitable" or no longer fit for someone to live in, "unoccupied" homes are structurally sound and habitable, but lack a resident (*Vital Signs 21*, n.d.).

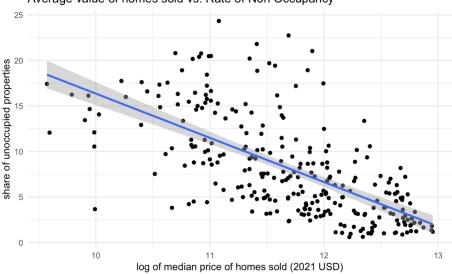
<sup>&</sup>lt;sup>10</sup> Figures 1-3 indicate point data, by CSA between 2015 and 2021, on the log of the median price of homes sold (adjusted to 2021 prices) and the share of (1) residential properties with rehabilitation permits, (2) demolition permits, and (3) unoccupied homes. The figures also include loess curve—locally estimated scatterplot smoothing—as a visual aid for the relationship between the two variables.



#### Figure 2. Neighborhoods with middle-to-lower home values tend to have more demolitions.

Source: Author's calculations using pooled data from First American Real Estate Solutions (FARES) and Baltimore Department of Housing and Community Development from 2015-2019. Calculations for adjusting prices to 2021 dollars can be found in Appendix C.3.

## Figure 3. There is a surplus of unoccupied homes in more affordable areas.



Average value of homes sold vs. Rate of Non Occupancy

Source: Author's calculations using pooled data from First American Real Estate Solutions (FARES) and Baltimore Department of Housing and Community Development from 2015-2019. Calculations for adjusting prices to 2021 dollars can be found in Appendix C.3.

These figures motivate my research question because they bring together a commonly studied *dependent* variable in crime literature (housing prices)<sup>11</sup> with commonly studied independent variables (housing market activity).<sup>12</sup> Without examining crime, Figures 1-3 indicate that certain activities may be responding to expected returns on investment. At the beginning of this study, I hypothesized that higher percentages of houses with rehabilitation permits would be in CSAs with lower median housing values. I thought that people may be incentivized to purchase these houses at a low price before renovating them for their own use. The findings in Figure 1, then, raised the question of how crime might be related to *lower* rates of rehabilitation permits in these areas. Additionally, at the beginning of this study, I hypothesized that demolitions would occur most frequently in areas with lower-value houses, as the first step in removing the abandoned structures.<sup>13</sup> While Figure 2 does demonstrate this relationship, the correlation is not nearly as strong as I expected. Indeed, the most demolitions seem to occur in CSAs with mid-value houses. This made me wonder if the crime rate had any relation to this trend. And finally, Figure 3 shows that more homes are unoccupied in areas with lower median housing values. This also made me wonder whether crime played a role, especially since I would otherwise expect more affordable homes to be occupied.<sup>14</sup>

<sup>&</sup>lt;sup>11</sup> Crime literature focused on housing prices include Thaler, 1978; Ceccato & Wilhelmsson, 2011, 2012, 2020; Clark & Cosgrove, 1990; Ihlanfeldt and Mayock, 2010; Buonanno et al., 2013.

<sup>&</sup>lt;sup>12</sup> Crime literature focusing on housing market activities include Freedman & Owens, 2011; Cantora et al., 2016; Iyer et al., 2020; Hipp et al., 2022; South et al., 2023.

<sup>&</sup>lt;sup>13</sup> Han (2014) finds that abandoned houses lower the value of nearby houses in Baltimore, using data from 1991 to 2010.

<sup>&</sup>lt;sup>14</sup> This expectation was informed by the national shortage of affordable housing. That is, because most low-income families face a lack of affordable housing options (Aurand et al., 2023), I expected a higher demand for lower-priced houses, leading to these properties being occupied rather than unoccupied.

#### 3. Literature Review

There is a recognized problem of endogeneity when it comes to studying crime, especially in urban areas (Ihlanfeldt & Mayock, 2010; Mallach, 2016; Kuhlmann, 2020). The literature focuses on how crime is the result of disorder, and how crime creates disorder which then contributes to more crime, creating a cycle of disrepair (Skogan, 1992; McGarrell et al., 1999; Sampson & Raudenbush, 1999). Before discussing the results of my study on the relationship crime has with potential avenues out of disorder, I frame the role of crime in urban decline through a discussion of the existing literature.

Most crime literature recognizes that crime is both a driver of urban decline and an outcome of it (Cancino, 2005; Ihlanfeldt & Mayock, 2010; de Boinville, 2012; Buonanno et al., 2013; Hipp & Wo, 2015). However, the literature overwhelmingly focuses on measuring results where crime is a dependent variable (Newman, 1972, 1973; Newman & Franck, 1982; Rosenbaum, 1986; Sampson et al., 1997; Cantora et al., 2016; Hipp et al., 2022). For example, foundational work in theories of why crime occurs (e.g. Social Disorganization Theory and Broken Windows) explains crime as the outcome of localized structural and social characteristics (Shaw & McKay, 1942; Wilson & Kelling, 1982).

Though there is an extensive focus on crime as an outcome, there are a number of studies where crime is the explanatory variable, though seemingly only as a determinant of home prices (Thaler, 1978; Clark & Cosgrove, 1990; Gibbons, 2004; Tita et al., 2006; Troy & Grove, 2008; Buonanno et al., 2013; Ceccato & Wilhelmsson, 2011, 2012, 2020). My study fills this gap in the literature by looking at crime as a determinant of individual, municipal, and community investment, rather than as a determinant of a piece of information such as price. I first summarize the literature with crime as the outcome variable, both in increasing crime contexts and

decreasing crime contexts. I then summarize the narrower literature on crime as the explanatory variable.

#### 3.1. Crime as an Outcome

There have been many academic contributions to the field of criminal activity, from which certain themes about the drivers of crime have emerged. An especially prevalent one is the role of the surrounding environment. Within that environment, two things have been extensively studied for their possible impact on crime: the tangible infrastructure, and the intangible sense of social cohesion. As will be explained in greater detail, more appealing infrastructure and well-maintained neighborhoods may reduce crime (South et al., 2023). Furthermore, a greater sense of community and collective efficacy may also reduce crime (Sampson et al., 1997).

## 3.1.1. Crime as the result of infrastructure and the built environment

Crime is often studied as an outcome of the surrounding physical environment. In 1972, Newman advanced the idea of "defensible space," a theory that posits that the physical design of residential spaces has a significant impact on the incidence of crime, along with resident's fear of future crime (Newman, 1972; Newman & Franck, 1982). When common spaces (e.g. community rooms in high-rise buildings) lack a clear owner, residents "cannot assert responsibility for their safety and maintenance, and these places are left vulnerable to crime and vandalism" (*Update from "Defensible Space" Pioneer Oscar Newman*, 1996). Research on this theory demonstrated that in low-income public housing projects, building height was among the top three most important predictors of robbery (Newman, 1973). Though these results have since been modified, the idea that architectural design and the surrounding environment may impact criminal behavior has long informed research (Brown & Bentley, 1993; South et al., 2023) and even public opinion today (Cantora et al., 2016; Hipp et al., 2022).

### 3.1.2. A reduction in crime as a result of investment in properties

**Rehabilitation Projects.** In Philadelphia, a randomized experiment was recently conducted empirically to quantify the benefits of rehabilitating signs of physical disorder and blight; specifically, the experiment tested whether the act of remediating abandoned properties can reduce crime. This study found that the properties with the highest level of remediation treatment had the biggest buffer against upward trends in gun violence (South et al., 2023). Thus, while a lack of investment and attention to physical infrastructure may exacerbate crime, improvements therein may indeed deter crime. Because this research implies that homeowners in high-crime areas may benefit from rehabilitating their property, especially if it is already in poor condition, my research question seeks to determine whether rehabilitation projects are indeed co-occurring with higher crime. If so, this literature indicates that these rehabilitation projects may soon facilitate a reduction in that crime.

**Demolitions.** Demolitions are an important tool for addressing vacant and abandoned properties, particularly those that are in such disrepair that they pose a physical danger to residents (Cohen, 2001). Demolitions can also help with the conditions of the surrounding environment—Kuhlmann (2020) finds that targeted demolitions of abandoned homes are associated with improvements in the physical condition of nearby homes. Notably, demolitions may also be helpful for addressing crime; frameworks of criminal theory suggest the presence of vacant residential buildings provides locations in which to carry out crimes unobserved (Becker, 1968; Spader et al., 2016). Demolishing these buildings, then, would get rid of these locations. Hence, I hope to uncover whether demolitions are a lever that policymakers use in response to high crime.

It is worth noting, though, that the literature on the efficacy of demolitions for reducing crime is mixed. Han and Helm (2023) find that "demolition of abandoned properties does not have any significant impact on nearby violent and property crime." Rather, a change in crime is attributable to differences in nearby socioeconomic and housing characteristics (ibid). However, Spader et al. (2016) find that demolitions reduced incidents of burglary and theft in Cleveland, a city similar to Baltimore in terms of its history of vacancy. Thus, for a city such as Baltimore, there may be a benefit of increasing demolitions for addressing dangerous vacant properties, but also for the potential to reduce crime. Hence, the question remains whether demolitions in Baltimore increase or decrease as a response to higher crime.

**Differentiating rehabilitation projects and demolitions.** Some existing literature on the relationship between investment and crime links together rehabilitation projects and demolitions in the conceptualizations of property investment (Lacoe et al., 2018; Smirniotis et al., 2022). This makes sense considering that rehabilitation projects might rely on the demolition of old buildings before the new ones can take root. However, it would be a mistake to completely merge these two variables. I find that rehabilitation permits and demolitions have opposing relationships to property prices (figures 2 and 3), suggesting that the two activities do not completely overlap. Thus, my study fills the gap in the literature created by the aggregation of rehabilitation projects and demolitions.

#### 3.1.3. Crime as the result of Social Disorganization

Crime is also studied as a response to social conditions. Shaw's and McKay's premier work on "social disorganization theory" posits that crime rates are based on factors that determine the level of "disorganization" in a neighborhood. Social disorganization can be defined as the inability of a community to realize the common values of its residents and maintain effective social controls (Bursik, 1988), and is commonly found in neighborhoods with high unemployment or structural decay (Shaw & McKay, 1942). Furthermore, this theory argues that a lack of social cohesion inhibits the sense that the community can work toward achieving common goals. Because combating crime is often a goal for neighborhoods, socially disorganized communities are unfortunately ineffective in doing so. Meanwhile, crime is more successfully addressed in socially organized communities (ibid).

**Broken Windows.** Shaw's and McKay's idea is echoed in one of the most infamous pieces of literature in the criminological sphere. In 1982, Wilson and Kelling released a piece in *The Atlantic*, detailing the framework of their "Broken Windows" theory of crime. They argue that when a community appears to be in decline visually (via attributes such as actual broken windows, graffiti, and/or trash), that is an invitation for more crime to occur. Essentially, the theory holds that if a community signals that it has a tolerance of minor disorders, it is signaling to criminals that delinquent behavior will go unreported and uncontrolled— similar to Shaw's and McKay's idea that crime is attributable to a lack of shared values which would empower the reporting and monitoring of crime. This concept is captured in the "broken windows" metaphor by the notion that one unrepaired broken window sets a precedent that invites further vandalism, leading to a progressive breakdown of community standards and making the area more susceptible to crime.

Since this article was released, many other studies have sought to either build off its findings or critique them.<sup>15</sup> One example of a continuation of this theory comes from Skogan (1992), who explored a "spiral of decay" wherein low levels of social cohesion contribute to

<sup>&</sup>lt;sup>15</sup> A notable critique of Broken Windows relates to the policing strategies borne out of the theory, which target small misdemeanors in hopes of preventing larger crime. These strategies have been shown to disproportionately affect people of color and are widely criticized for fostering racial profiling and brutality. For more on critiques of Broken Windows policing, specifically in Baltimore, see Collins 2007.

crime, and higher levels of crime also contribute to low levels of social cohesion and collective efficacy. Viewed in reverse, efforts to increase a local sense of collective efficacy, then, are important for increasing social organization, which Skogan argues is an important aspect of crime prevention. This argument was informally tested in a Baltimore neighborhood in 2013. Though the program's effect on crime is hard to isolate, the comprehensive set of initiatives in the program is argued to be the reason the neighborhood saw an "impressive" 500-day period without any homicides (Iyer et al., 2020, p. 24).

Based on this literature, social/community disinvestment may be directly related to the rate of unoccupied homes. If large shares of homes are unoccupied, this facilitates a sense of social isolation and disorder, which in turn contributes to low levels of social cohesion and collective efficacy (Garvin et al., 2013). Indeed, case studies of Baltimore show that residents attribute social disorder to low levels of engagement from neighbors (Cantora et al., 2016). As a result, they then feel fewer incentives to contribute to their neighborhood (ibid). Thus, the prevalence of unoccupied homes may be the best quantitative proxy for community disinvestment.

### 3.2. Crime as the Cause: Crime's Impact on Communities and Property Values

Despite the focus of crime literature on crime as an outcome variable, there is a branch of the literature that looks at crime as an explanatory variable, but specifically in relation to housing prices and neighborhood value. In accordance with the literature establishing a positive trend between disorder (both physical and social) and crime, the reversal of this relationship yields similar results. That is, the prevalence of crime creates a sense of decline, which decreases demand for properties and homes in the neighborhood (Buonanno et al., 2013), which is then demonstrated by lower property values in higher-crime neighborhoods (Thaler, 1978; Ceccato &

Wilhelmsson, 2011, 2012, 2020; Clark & Cosgrove, 1990; Ihlanfeldt and Mayock, 2010). Furthermore, crime and the less-tangible fear of crime lead to flight from the city into the suburbs (Massey & Denton, 1993; Tita et al., 2006). In sum, this literature asserts that as crime increases, neighborhood appeal and home values will decline.

## 3.3. Gap in the Literature

The literature on crime and housing overwhelmingly uses crime as the dependent variable. For the literature that places crime as an independent variable, however, crime's explanatory role seems to be exclusively in relation to the price of homes rather than other measures of neighborhood conditions. My study fills the gap in the literature by looking at crime as the independent variable of interest in relation to measures or proxies of residential investments, which are another signal of neighborhood vitality beyond home prices.

To my knowledge, only one other study has looked at crime as an explanatory variable for property investment (Lacoe et al., 2018). Using a differences-in-differences approach with data from Chicago and Los Angeles, they find that a reduction in crime leads to an increase in investment. They look at investment through the issuance of new building permits in aggregate. My study builds on this by examining permits that are specifically for the rehabilitation of existing residential properties and those that are for the demolition of existing residential properties (as well as including a proxy for social disinvestment). The independent investigations of the relationship these permits have with crime allow me to see whether the overall trend found by these researchers changes when breaking down investment into these categories. Additionally, setting my study in Baltimore—a different city with a different relationship to crime and property interventions—offers a novel perspective on how investment may respond to crime.

#### 4. Data

To study how crime relates to investment and disinvestment in residential properties and neighborhoods, I use Baltimore's Department of Housing and Community Development (DHCD) data, Baltimore Police Department (BPD) data, and US Census Bureau data from the American Community Survey (ACS). These data are downloaded from the Baltimore Neighborhood Indicators Alliance (BNIA) Open Data Portal. BNIA collects data from reputable sources and publishes "Vital Signs" on this portal to help measure progress towards meaningful outcomes at the community level (*Vital Signs 21*, n.d.). Data is available for years 2015-2021 for over 150 indicators.

Based on my review of the literature, I focus my study on three key variables that capture investment through their role in maintaining physical and social order: 1) the prevalence of rehabilitation permits, 2) the prevalence of demolition permits, and 3) the prevalence of unoccupied homes. These variables serve as proxies for investment that will help answer my question of how crime relates to investment and disinvestment in residential properties.

In this study, Community Statistical Areas (CSAs) are the unit of observation rather than neighborhoods. CSAs are built on census tracts, which are small permanent statistical subdivisions of counties that are composed of an average of 4,000 residents.<sup>16</sup> CSAs are designed to capture demographic homogeneity while reflecting resident perceptions of community boundaries (Appendix A). Thus, for my study, this unit of analysis should be sufficiently granular to capture the relationship between crime and investment in a particular CSA without systematically masking minority trends.

<sup>&</sup>lt;sup>16</sup> Census tracts should contain a minimum of 1,200 residents and a maximum of 8,000 residents (*Glossary*, n.d.).

Table 1 presents the name and category of each variable I use, the source description of how this variable is measured, and the available years I used in my model. My first outcome variable of interest is the share of residential properties within a CSA that have a permit for a rehabilitation project exceeding \$5,000 in total cost. The threshold of \$5,000 is used by the DHCD to differentiate minor renovations from more significant projects. Thus, the count of rehabilitation permits captured in this variable represents more substantial projects than a new coat of paint. Given that the median household income in Baltimore was \$58,349,<sup>17</sup> a \$5,000 rehabilitation project would pull nearly 10% of the average household's annual income. Hence, this variable is a strong proxy for an owner's investment in their property.

Data on demolitions also comes from Baltimore DHCD, showing the number of permits issued for the demolition of residential buildings per 1,000 existing residential properties. The city uses demolitions to address vacant properties, specifically those that are so unstable that they pose a safety risk to residents walking nearby (*Baltimore's Collection Of Vacant Houses*, 2022). Because demolitions are an important tool for the city to address vacancies, they represent municipal-level investment in improving and maintaining physical order.

For capturing my third variable of interest, social disinvestment, I use data on unoccupied homes collected by the US Postal Service (USPS) and Baltimore DHCD. Homes are considered unoccupied when the postal service finds that there has been no mail collection (sent or received) at the property for at least 90 days. Though there are some limitations for this data in measuring non-occupancy—for example, units may be counted as unoccupied if the residents receive their mail at a separate PO Box—this data has been used as a proxy for vacant or unoccupied homes in many studies (Molloy, 2016; Immergluck, 2016; Wang & Immergluck, 2019). Furthermore,

<sup>&</sup>lt;sup>17</sup> This estimate comes from the American Community Survey 5-year estimate table for 2018-2022 (U.S. Census Bureau).

Silverman et al. (2013) list many arguments for the advantages of using USPS data in this form, rather than census data, to measure non-occupancy. Among them are the benefits of having current data based on full counts of all addresses in an area and the benefits of having data from a source that subdivides properties by residential, business, and other types (ibid).

Furthermore, even though electronic forms of communication are increasingly used, mail delivered by the USPS is still essential for the delivery of official documents such as a jury summons, voter registrations, and mail ballots. If there is a large portion of citizens who are not receiving mail, even if they are still occupying their homes, it may be a sign that they are not engaging with their community. Thus, higher rates of non-occupancy may capture higher levels of social disinvestment.

The explanatory variables of interest in my study are the various crime rates, which are reported by the Baltimore Police Department. Baltimore classifies most major crimes homicide, rape, aggravated assault, robbery, burglary, larceny, and auto theft—as "Part 1" crime. BPD also reports whether the crime is identified as violent (homicide, rape, aggravated assault, and robbery) or property-related (burglary, larceny, and auto theft). Hence, shares of violent and property crime should sum to the total Part 1 crime. Data are reported as a rate: the number of incidents per 1,000 residents. I touch on some limitations of this crime data in Section 6.6.

Control variables for race, ethnicity, age, education, employment, and poverty status are obtained from the American Community Survey, an ongoing survey conducted by the U.S. Census Bureau to capture moving averages of demographic and housing indicators. The survey is administered every year and is the best representation of up-to-date demographic and housing conditions at the CSA level.

| Variable<br>Name  | Variable<br>Type | Description  | Source and Years   |
|---|------------------|--|--|
|   |                  | HOUSING  |  |
| Percentage of<br>Properties with<br>Rehabilitation<br>Permits<br>Exceeding<br>\$5,000 | Outcome          | The percent of residential properties that have<br>applied for and received a permit to renovate<br>the interior and/or exterior of a property where<br>the cost of renovation will exceed \$5,000.<br>The threshold of \$5,000 is used to differentiate<br>a minor renovation project from a more<br>significant renovation project.  | Source: Baltimore Department<br>of Housing and Community<br>Development<br>Years Used: 2015, 2016, 2017,<br>2018, 2019, 2020, 2021       |
| Number of<br>Demolition<br>Permits per<br>1,000<br>Residential<br>Properties          | Outcome          | The number of permits issued for the<br>demolition of residential buildings per 1,000<br>existing residential properties.<br>The permits are analyzed by date of issue and<br>not date of actual demolition.   | Source: Baltimore Department<br>of Housing and Community<br>Development<br>Years Used: 2015, 2016, 2017,<br>2018, 2019, 2020, 2021       |
| Percent of<br>Residential<br>Properties that<br>are<br>Unoccupied                     | Outcome          | The percentage of residential addresses for<br>which the United States Postal Service has<br>identified as being unoccupied (no mail<br>collection) for a period of at least 90 days or<br>longer.   | Source: U.S. Postal Service,<br>U.S. Department of Housing<br>and Urban Development<br>Years Used: 2015, 2016, 2017,<br>2018, 2019, 2020 |
| Median Price<br>of Homes Sold   | Descriptive      | The median home sales price is the middle<br>value of the range of prices for which homes<br>are sold (both market and private transactions)<br>within a calendar year.<br>The median value is used as opposed to the<br>average so that outliers (extremely high and<br>extremely low prices) do not skew the prices<br>for which homes are sold. This measure does<br>not take into account the assessed value of a<br>property. | Source: First American Real<br>Estate Solutions (FARES)<br>Years Used: 2015, 2016, 2017,<br>2018, 2019                                   |
|   |                  | CRIME  |  |
| Part 1 Crime<br>Rate  | Explanatory      | The Part 1 crime rate captures incidents of<br>homicide, rape, aggravated assault, robbery,<br>burglary, larceny, and auto theft that are<br>reported to the Police Department, per 1,000<br>residents.  | Source: Baltimore Police<br>Department<br>Years Used: 2015, 2016, 2017,<br>2018, 2019, 2020, 2021  |
| Violent Crime<br>Rate   | Explanatory      | A subset of Part 1 crimes identified as being<br>violent (homicide, rape, aggravated assault,<br>and robbery), per 1,000 residents   | Source: Baltimore Police<br>Department<br>Years Used: 2015, 2016, 2017,<br>2018, 2019, 2020, 2021  |

# Table 1. Description of Variables in Model

| Property<br>Crime Rate                                      | Explanatory                    | A subset of Part 1 crimes identified as being<br>property-based (burglary and auto theft), per<br>1,000 residents   | Source: Baltimore City Police<br>Department<br>Years Used: 2015, 2016, 2017,<br>2018, 2019, 2020, 2021  |
|---|--------------------------------|---|---|
|   |                                | RACE  |   |
| Percent of<br>Residents,<br>Black or<br>African<br>American | Control                        | The total number of persons that identify<br>themselves as being racially Black or African<br>American (and ethnically non-Hispanic) out of<br>the total number of persons living in a CSA.<br>"Black or African American" refers to a<br>person having origins in any of the Black<br>racial groups of Africa. It includes people who<br>indicated their race as "Black."  | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019, 2020,<br>2017-2021 |
| Percent of<br>Residents,<br>White                           | Control,<br>Reference<br>group | The percentage of persons, out of the total<br>number of persons living in an area,<br>self-identifying as racially White (and<br>ethnically non-Hispanic).<br>"White" refers to a person having origins in<br>any of the original peoples of Europe, the<br>Middle East, or North Africa. This indicator<br>includes people who identified their race(s) as<br>"White."  | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019, 2020,<br>2017-2021 |
| Percent of<br>Residents,<br>Hispanic or<br>Latino           | Control                        | The percentage of persons, out of the total<br>number of persons living in an area,<br>self-identifying their ethnicity as Hispanic or<br>Latino.<br>Hispanic origin can be viewed as the heritage,<br>nationality group, lineage, or country of birth<br>of the person or the person's parents or<br>ancestors before they arrived in the United<br>States. People who identify their origin as<br>Hispanic, Latino, or Spanish may be of any<br>race. | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019, 2020,<br>2017-2021 |
| Percent of<br>Residents,<br>Asian                           | Control                        | The percentage of persons, out of the total<br>number of persons living in an area,<br>self-identifying as Asian (and non-Hispanic).<br>"Asian" refers to a person having origins in<br>any of the original peoples of the Far East,<br>Southeast Asia, or the Indian subcontinent,<br>including, for example, Cambodia, China,<br>India, Japan, Korea, Malaysia, Pakistan, the<br>Philippine Islands, Thailand, and Vietnam.                           | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019, 2020,<br>2017-2021 |

| Percent of<br>Residents, Two<br>or more races     | Control | The percentage of persons, out of the total<br>number of persons living in an area, who<br>self-identify as being of two or more races<br>(non-Hispanic).  | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019, 2020,<br>2017-2021      |
|---|---------|--|--|
| Percent of<br>Residents, All<br>other races       | Control | The percentage of persons, out of the total<br>number of persons living in an area, who<br>self-identify as either American Indian,<br>Alaskan Native, Native Hawaiian or Other<br>Pacific Islander, or some other race<br>(non-Hispanic). | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019, 2020,<br>2017-2021      |
|   | -       | AGE  |  |
| Percent of<br>Population,<br>Under 5 Years<br>old | Control | The percent of persons, out of all persons<br>living in an area, aged 5 years and under.   | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019,<br>2016-2020, 2017-2021 |
| Percent of<br>Population,<br>age 5-17             | Control | The percent of persons, out of all persons living in an area, aged 5 to 17 years.  | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019,<br>2016-2020, 2017-2021 |
| Percent of<br>Population,<br>age 18-24            | Control | The percent of persons, out of all persons<br>living in an area, aged 18 to 24 years.  | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019,<br>2016-2020, 2017-2021 |
| Percent of<br>Population,<br>age 25-64            | Control | The percent of persons, out of all persons living in an area, aged 25 to 64 years.   | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019,<br>2016-2020, 2017-2021 |

| Percent of<br>Population,<br>Over 65 years<br>old   | Control,<br>Reference<br>group | The percent of persons, out of all persons<br>living in an area, 65 years and above.  | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019,<br>2016-2020, 2017-2021 |
|---|--------------------------------|---|--|
|   |                                | EDUCATION   |  |
| Percent of<br>Population (25<br>years and<br>over) with less<br>than High<br>School<br>diploma                                    | Control,<br>Reference<br>group | The percentage of persons that have not<br>completed, graduated, or received a high<br>school diploma or GED.<br>This is a standard indicator used to measure<br>the portion of the population with less than a<br>basic level of skills needed for the workplace.<br>Persons under the age of 25 are not included in<br>this analysis since many of these persons are<br>still attending various levels of schooling.  | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019,<br>2016-2020, 2017-2021 |
| Percent of<br>Population (25<br>years and<br>over) with<br>High School<br>diploma and<br>Some College<br>or Associate's<br>Degree | Control                        | The percentage of persons that have<br>completed, graduated, or received a high<br>school diploma or GED and also have taken<br>some college courses or completed their<br>Associate's degree.<br>This is a standard indicator used to measure<br>the portion of the population with a basic level<br>of skills needed for the workplace. Persons<br>under the age of 25 are not included in this<br>analysis since many of these persons are still<br>attending various levels of schooling. | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019,<br>2016-2020, 2017-2021 |
| Percent of<br>Population (25<br>years and<br>over) with a<br>Bachelor's<br>Degree or<br>Above                                     | Control                        | The percentage of persons that have<br>completed, graduated, or received a<br>Bachelor's or an advanced degree.<br>This is an indicator used to measure the<br>portion of the population having an advanced<br>level of skills needed for the workplace.<br>Persons under the age of 25 are not included in<br>this analysis since many of these persons are<br>still attending various levels of schooling.  | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019,<br>2016-2020, 2017-2021 |

| EMPLOYMENT  |         |   |  |
|---|---------|---|--|
| EMPLOYMENI  |         |   |  |
| Percent of<br>Population<br>(16-64) that<br>are Employed                  | Control | The percent of persons between the ages of 16<br>and 64 formally employed or self-employed<br>and earning a formal income.<br>It is used to understand how many persons are<br>working out of the entire population, not just<br>those in the labor force (persons who may be<br>looking for work or working).  | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019,<br>2016-2020, 2017-2021 |
|   |         | INCOME  |  |
| Median<br>Household<br>Income   | Control | Median household income is the middle value<br>of the incomes earned in the prior year by<br>households in an area. Income is adjusted to<br>2021 dollars (Appendix C.2).<br>The median value is used as opposed to the<br>average so that both extremely high and<br>extremely low prices do not distort the total<br>amount of income earned by households in an<br>area.   | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019,<br>2016-2020, 2017-2021 |
|   | -       | POVERTY   |  |
| Percent of<br>Family<br>Households<br>Living Below<br>the Poverty<br>Line | Control | Percent of family households living below the<br>poverty line measures the percentage of<br>households, out of all households in an area,<br>whose income fell below the poverty<br>threshold.<br>Federal and state governments use such<br>estimates to allocate funds to local<br>communities. Local communities use these<br>estimates to identify the number of individuals<br>or families eligible for various programs. | Source: U.S. Census Bureau,<br>American Community Survey<br>Years Used: 2011-2015,<br>2012-2016, 2013-2017,<br>2014-2018, 2015-2019,<br>2016-2020, 2017-2021 |

## 5. Methodology

To examine how crime is associated with investment and disinvestment in residential properties and neighborhoods, I run a series of OLS fixed effects models with three dependent variables—the percentage of rehabilitation permits, the percentage of demolition permits, and the prevalence of unoccupied homes. Using two-way fixed effects controls for variation across both time and space (in this case, CSAs). I run each model three times, once for each breakdown of

crime: total Part 1 crime, Part 1 crime that is violent, and Part 1 crime that is property-related (equations 1-9 and tables 2-4). I also employ additional controls for race, ethnicity, age, education, employment, and poverty status. By including these controls, I am improving the fit of the model and explanatory power of crime in my model (Wooldridge, 2016).

I created a panel data set with 7 years of data (2015-2021) for 55 Community Statistical Areas (CSAs), giving me a balanced panel of 385 observations. One exception is the data on unoccupied homes; there is no data available for 2021. To account for this, the model for this variable only uses the balanced panel of 330 observations, from 2015-2020.

An important consideration when working with crime data as an explanatory variable is the possibility of time-lagged responses. For reasons of both feasibility and delayed reactions, residents may be slow to invest or disinvest in properties following a crime incident. Lacoe et al. (2018) consider this when they study the impact of crime on building investment in Chicago and Los Angeles and find that a one-year lag for crime is appropriate. Accordingly, I regress the current year's observations of investment and disinvestment on crime in the previous period. This allows the model to answer my research question more precisely by relating investment activities to crime in the previous period, as per previous literature's findings.

#### 5.1. Percent of Properties with Rehabilitation Permits

I first consider the relationship between total Part 1 crime in the previous period and the percentage of properties with rehabilitation permits in the current period. I then break up this analysis to find the relationship between rehabilitation and violent crime, as well as rehabilitation and property crime. Equations 1-3 illustrate the models.

$$\% rehabs_{CSA, t} = \beta_1 part 1 crime_{CSA, t-1} + \sum_{i=2\dots k}^{K} \beta_i X_{CSA, t} + \gamma_{CSA} + \delta_t + \varepsilon_{CSA, t}$$
(eq. 1)

$$\% rehabs_{CSA,t} = \beta_1 violent \ crime_{CSA,t-1} + \sum_{i=2\dots k}^{K} \beta_i X_{CSA,t} + \gamma_{CSA} + \delta_t + \varepsilon_{CSA,t}$$
(eq. 2)

$$\% rehabs_{CSA, t} = \beta_1 property crime_{CSA, t-1} + \sum_{i=2\dots k}^{K} \beta_i X_{CSA, t} + \gamma_{CSA} + \delta_t + \varepsilon_{CSA, t} \quad (eq. 3)$$

where  $X_{CSA, t}$  is a vector of control variables representing shares of the population by: age, race, ethnicity, education attainment, employed status, and living below the poverty line.  $\gamma_{CSA}$ accounts for the effects on the percentage of properties with rehabilitation permits for any factors that are constant within community statistical areas over the timeframe of the study. The year fixed effects,  $\delta_t$ , account for macroeconomic factors that affect the percentage of properties with rehabilitation permits similarly across all community statistical areas but differ by year, and  $\varepsilon_{CSA, t}$ is the idiosyncratic error term.

#### 5.2. Percent of Properties with Demolition Permits

Next, I model the relationship between the three types of crime in the previous period and the rate of demolition permits in the current period. Equations 4-6 show these models:

$$demolitions_{CSA, t} = \beta_1 part \ 1 \ crime_{CSA, t-1} + \sum_{i=2\dots k}^{K} \beta_i X_{CSA, t} + \gamma_{CSA} + \delta_t + \varepsilon_{CSA, t}$$
(eq. 4)

$$demolitions_{CSA, t} = \beta_1 \ violent \ crime_{CSA, t-1} + \sum_{i=2\dots k}^{K} \beta_i X_{CSA, t} + \gamma_{CSA} + \delta_t + \varepsilon_{CSA, t} (eq. 5)$$

$$demolitions_{CSA, t} = \beta_1 property crime_{CSA, t-1} + \sum_{i=2\dots k}^{K} \beta_i X_{CSA, t} + \gamma_{CSA} + \delta_t + \varepsilon_{CSA, t}$$
(eq. 6)

where  $X_{CSA, t}$  is a vector of control variables representing shares of the population by: age, race, ethnicity, education attainment, employed status, and living below the poverty line.  $\gamma_{CSA}$  accounts for the effects on the percentage of properties with rehabilitation permits for any factors that are constant within community statistical areas over the timeframe of the study. The year fixed effects,  $\delta_t$ , account for macroeconomic factors that affect the rate of demolition permits similarly across all community statistical areas but differ by year, and  $\varepsilon_{CSA, t}$  is the idiosyncratic error term.

## 5.3. Prevalence of Unoccupied Residential Properties

I then look at the relationship between the one-year lag of three types of crime and the prevalence of unoccupied properties in the current period. Equations 7-9 illustrate these models:

$$\% unoccupied_{CSA, t} = \beta_1 part 1 crime_{CSA, t-1} + \sum_{i=2\dots k}^{K} \beta_i X_{CSA, t} + \gamma_{CSA} + \delta_t + \varepsilon_{CSA, t}$$
(eq. 7)

% unoccupied<sub>CSA,t</sub> = 
$$\beta_1$$
 violent crime<sub>CSA,t-1</sub> +  $\sum_{i=2...k}^{K} \beta_i X_{CSA,t}$  +  $\gamma_{CSA}$  +  $\delta_t$  +  $\varepsilon_{CSA,t}$  (eq. 8)

% unoccupied<sub>CSA,t</sub> = 
$$\beta_1$$
 property crime<sub>CSA,t-1</sub> +  $\sum_{i=2...k}^{K} \beta_i X_{CSA,t}$  +  $\gamma_{CSA}$  +  $\delta_t$  +  $\varepsilon_{CSA,t}$  (eq. 9)

where  $X_{CSA, t}$  is a vector of control variables representing shares of the population by:

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age, race, ethnicity, education attainment, employed status, and living below the poverty line.  $\gamma_{CSA}$  accounts for the effects on the prevalence of unoccupied properties that are constant within community statistical areas over the timeframe of the study and that have an additive impact. The year fixed effects,  $\delta_{t'}$  account for macroeconomic factors that affect the prevalence of unoccupied properties similarly across all community statistical areas but differ by year, and  $\varepsilon_{CSA,t}$  is the idiosyncratic error term.

## 5.4. Assumptions of the model

There are two key assumptions of these models. The first is that the prevalence of each of the dependent variables (rehabilitation permits, demolition permits, and unoccupied houses) is affected linearly by the independent variables in the model. The second is that the unobservable factors affecting the prevalence of the dependent variables can be decomposed into components that vary over time but not across CSAs (year fixed effects), components that vary across CSAs but do not vary across time (CSA fixed effects), and an idiosyncratic component that varies over time and across CSAs and is not correlated with the independent variables in the model.

Though I control for a wide set of variables, the design of my model does not allow for a causal interpretation of the relationship between crime and investment, due to the endogeneity of crime. However, it is important to note that even though my model is not causal, the results are not necessarily symmetric. Specifically, it is not valid to assert that the relationship of crime influencing investment can simply be reversed to imply that investment similarly influences crime. The mechanisms driving each direction of influence may differ significantly. This distinction is crucial for my discussion of the results, as I will explore the potential implications of the observed relationship between crime and investment on the hypothesized, yet unobserved, effects of investment on crime and disorder in Baltimore.

## 5.5. Choropleth Maps of Dependent and Independent Variables in the Models

I created maps of Baltimore City's CSAs using data from 2015-2021 (unless otherwise indicated) for select variables (Total Part 1 Crime, Violent Crime, Property Crime, Rehabilitation Rate, Demolition Rate, Non-occupancy Rate, Share of Black Residents, Share of White Residents, Share of Residents of All Other Races, and Share of Residents Living Below the Poverty Line). I used the quantile classification method to create equal proportions of data in each of the 5 categories for the first year of data displayed on the map. Then, to indicate how the data changes over time, I impose the same quantile classifications (allowing for CSAs to move between the 5 categories) on the remaining years of data for that variable (Brewer & Pickle, 2002). The maps thus clearly display the variation between CSAs and the trends over time (see Appendices F.1-F.10).

#### 6. Results and Discussion

The results proceed as follows: first, I discuss some descriptive statistics about the demographic makeup across the different CSAs in Baltimore, specifically those statistics that are significant controls in my model (section 6.1). I then analyze the results from my models, beginning with the relationship between the lagged crime rate and the rate of rehabilitation permits (section 6.2). I follow that with a discussion of the relationship between the lagged crime rate and the rate of demolitions (section 6.3). Finally, I discuss the relationship between lagged crime and the prevalence of unoccupied homes (section 6.4).

In my discussion of the results, I focus on the immediate relationship the crime rate has with the different proxies for investment as demonstrated in my model, and I discuss the implications of these relationships for the outlook of Baltimore in relation to crime and housing conditions. My findings are mostly aligned with the patterns discussed in the existing crime literature, which at a high level demonstrate that physical and social disorder go hand-in-hand with crime. However, my results contain a notable exception—I find that in areas with a higher crime rate, there may be a *reduction* in physical disorder via a higher prevalence of rehabilitation projects. I discuss what this surprising result means in the context of Baltimore and the implications for the city's policy plans for crime reduction and housing market revitalization.

#### **6.1. Demographic Distributions**

Because I am working with panel data, the best way to display the demographics of Baltimore is with maps. Figure 4 displays the share of black residents in each CSA during my study period (2015 and 2021). The shades correspond to quantile breaks in the data based on 2015 distributions. Figure 5 displays the share of white residents in the same manner. Note that the areas with a majority of white residents are the same areas where blacks are significantly in the minority. Note also that the distribution of black residents is right-skewed—the second quantile already captures majority-black neighborhoods. On the other hand, the distribution for whites is left-skewed, with only the top two quantiles capturing majority-white neighborhoods. Figure 6 demonstrates the share of all other races in 2015 and 2021. There is a noticeable change in the distribution compared to 2015 levels, but it is likely due to this group's low share of the population—never more than 6% in any one CSA. Therefore, the distribution of this group will be more sensitive to noise.

Figure 7 displays the share of residents living below the poverty line in 2015 and 2021. This distribution represents the number of families whose annual income falls below the threshold for poverty set by the federal government. Though the official poverty thresholds do not vary geographically, they are updated annually for inflation. Poverty measures are not intended to be a complete measure of what a family needs for subsistence; rather, they are intended for statistical analysis (*How the Census Bureau Measures Poverty*, n.d.). Therefore, this map demonstrates the geographic distribution of households that are income-constrained, and likely unable to individually invest in their properties. Areas with much lower shares of families in poverty overlap tend to overlap with areas with higher populations of white residents, specifically the mid-northern area of Baltimore.

Figure 8 displays the distribution of total Part 1 crime in Baltimore, in 2015 and 2021. CSAs with higher rates of crime appear to align with CSAs that have higher shares of residents in poverty. Total crime visibly decreased from 2015 to 2021, with an especially large change in 2020. This supports my use of the COVID dummy<sup>18</sup> in the robustness checks, though those

<sup>&</sup>lt;sup>18</sup> The onset of COVID may have reduced crime incidents given Stay-at-Home orders which encouraged people to isolate and remain indoors (Exec. Order No. 20-05-06-01). Further, COVID may have had an impact on the rate of housing rehabilitations, demolitions, and non-occupancy, but such an impact is not as visible in the choropleth maps.

results do not vary from my main results (Appendices E.1-E.3). Additionally, the rate of violent crime (Appendix F.2) does not appear to decrease as much as total crime (Appendix F.1) and property crime (Appendix F.3). While not the focus of my research question, this is an observation to keep in mind when looking at the results of my model. Particularly, the coefficients are of larger magnitude for violent crime, suggesting that investment is more responsive to violent crime.

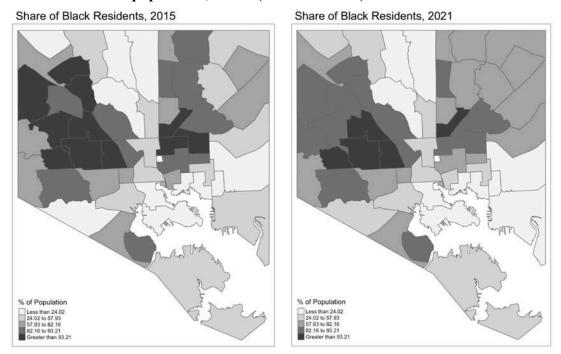
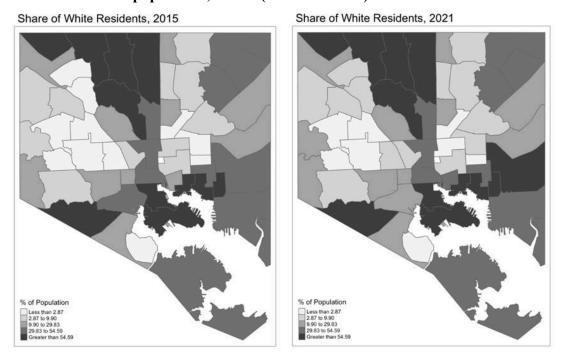


Figure 4. Percent of the population, Black (2015 and 2021)

Note: The minimum from 2015 to 2021 is 1.73%, and the maximum is 97.44%. Source: Author's calculations of US Census American Community Survey data (2015 and 2021).



## Figure 5. Percent of the population, White (2015 and 2021)

Note: The minimum from 2015 to 2021 is 0.22%, and the maximum is 90.63%. Source: Author's calculations of US Census American Community Survey data (2015 and 2021).

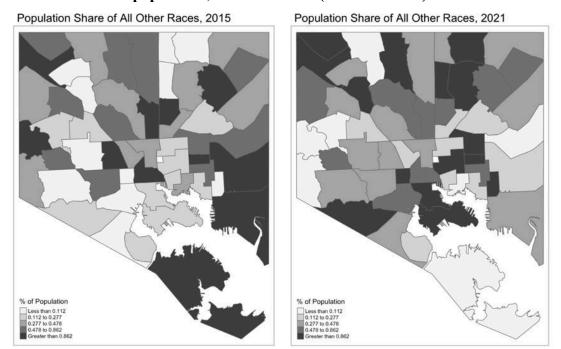
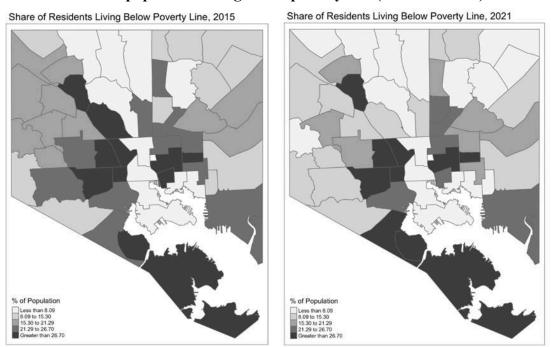


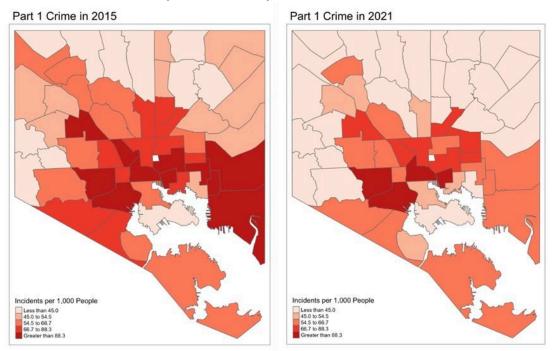
Figure 6. Percent of the population, All other races (2015 and 2021)

Note: The minimum from 2015 to 2021 is 0.00%, and the maximum is 5.22%. Source: Author's calculations of US Census American Community Survey data (2015 and 2021).



## Figure 7. Percent of the population living under poverty line (2015 and 2021)

Note: The minimum from 2015 to 2021 is 0.00%, and the maximum is 48.72%. Source: Author's calculations of US Census American Community Survey data (2015 and 2021).



## Figure 8. Total Part 1 Crime (2015 and 2021)

Note: The minimum from 2015 to 2021 is 10.14 incidents, and the maximum is 312.75 incidents. Source: Author's calculations of Baltimore Police Department data (2015 and 2021).

### 6.2. Percent of Properties with Rehabilitation Permits

Table 2 shows that the previous year's crime rate (t-1) has a significant positive relationship with the prevalence of rehabilitation permits in the current year (t). If the total crime rate (per 1,000 residents) in time period t-1 increases by 10%, the rate of rehabilitation permits in time t increases by 0.1%, on average. Looking specifically at the violent crime rate (per 1,000 residents) in time period t-1, a 10% increase is associated with a 0.2% increase in the rehabilitation rate in time t, on average. Finally, a 10% increase in property crime (per 1,000 residents) in time period t-1 is associated with a 0.1% increase in the rehabilitation rate in time t, on average. Finally, a 10% increase in the rehabilitation rate in time t, on average. Finally, a 10% increase in the rehabilitation rate in time t, on average. All results are statistically significant, meaning we can confidently conclude that the relationships are positive and non-zero.

Choropleth maps of the change in rehabilitation rates across years and CSAs show a noticeable increase in the prevalence of rehabilitation permits from 2015 to 2021 (Appendix F.4), offering support for the rationality of the positive coefficient. However, it is important to note that the maps of rehabilitation permits serve as a visual aid and do not contain the control variables in the model. Thus, on their own, the maps do not show the relationship rehabilitation permits have to crime.

| Crime and Rehabilitation Permits |   |           |             |
|----------------------------------|---|-----------|-------------|
|                                  | Dependent variable:<br>Rate of Rehabilitation Permits |           |             |
|                                  |   |           |             |
|                                  | (1)   | (2)       | (3)         |
| Lag of Total Crime               | $0.008^{**}$  |           |             |
|                                  | (0.003)   |           |             |
| Lag of Violent Crime             |   | 0.021**   |             |
|                                  |   | (0.010)   |             |
| Lag of Property Crime            |   |           | $0.010^{*}$ |
|                                  |   |           | (0.005)     |
| Demographic Controls             | Yes   | Yes       | Yes         |
| Year Fixed Effects               | Yes   | Yes       | Yes         |
| CSA Fixed Effects                | Yes   | Yes       | Yes         |
| # of CSAs                        | 55  | 55        | 55          |
| Observations                     | 384   | 384       | 384         |
| R <sup>2</sup>                   | 0.087   | 0.084     | 0.081       |
| Adjusted R <sup>2</sup>          | -0.131  | -0.136    | -0.140      |
| Note:                            | *p<0.1;   | **p<0.05; | ****p<0.01  |

 Table 2. Relationship between lagged crime and the prevalence of rehabilitation permits in a CSA

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Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at p<0.1, p<0.05, p<0.01. 384 observations are used from the full panel of 385 observations due to the one-year lag on crime. Results rendered with stargazer (Hlavac, 2022). Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

The results indicate that areas with higher crime tend to have more rehabilitation permits, suggesting that these higher-crime areas may be seeing more individual-level investment than lower-crime areas. This is a surprising finding, given that the literature establishes a relationship where crime is inversely related to physical order (Wilson and Kelling, 1982), suggesting that crime facilitates a lack of investment. Lacoe et al. (2018) find such a relationship in their studies of Chicago and Los Angeles. However, my findings indicate an opposite relationship—that investment happens even in areas with more prevalent crime.

This relationship is promising for the future of communities with higher crime. Though my study does not identify the mechanisms by which this investment is being promoted, it nonetheless shows that high-crime areas are not necessarily doomed for further physical decay. Rather, they may soon be benefitting from physical improvements as a result of the higher rates of rehabilitation permits.

One potential explanation for this surprising result that would nullify my interpretation would be the presence of an exogenous policy that incentivized rehabilitation in neighborhoods with more disorder and blight. However, to the best of my knowledge, such a policy did not exist in Baltimore during the period of the study. Another potential hypothesis is that people are purchasing cheap properties in areas of disorder and/or blight to renovate them and sell them for profit. If this were the case, the association between prices of homes sold and the rehabilitation rate (Figure 1) would likely be unclear; however, the relationship depicted in figure 1 is clearly upward sloping. Thus, it is hard to defend this hypothesis without data on the dates of the home sales.

For an additional affirmation of the model, I checked the signs of the coefficients on the control variables to confirm the rationality of the trends, given my understanding of the literature (the full results of the model can be found in Appendix D). Review of these coefficients indeed supports the model. For example, the coefficient on the share of black residents is negative (Appendix D.1). This indicates that in reference to the share of white residents,<sup>19</sup> as the share of black residents increases in an area, the rate of rehabilitation projects will decrease. The maps showing the rehabilitation rates and the share of black residents (Appendices F.4 and F.7) provide some visual validation of this result. Particularly, the CSAs in the central-western part of the city,

<sup>&</sup>lt;sup>19</sup> The share of white residents serves as the reference group for race and ethnicity in my model.

which tend to be majority black, do not reach the top quintile for rehabilitation permits until 2020, indicating a period of disproportionate underinvestment.

With Baltimore's history of redlining (Pett, 2021), perhaps this result is not surprising, though it is disappointing. With such a large share of black residents—57% of Baltimore's population in 2020—it suggests that a significant portion of the city's population may be living in areas that are not receiving equitable investment via housing and infrastructure rehabilitation. This disparity contributes to a spiral of decline, one that rehabilitation would be poised to address. Encouraging or subsidizing rehabilitation projects in these areas may address the historical inequities and allow black homeowners to build their wealth—a practice from which they were systematically denied in the 20th century (Pappoe, 2016).

#### 6.3. Percent of Properties with Demolition Permits

Table 3 shows that as the previous year's (t-1) crime rate (per 1,000 residents) increases, demolition permits (per 1,000 properties) in the current year (t) decrease on average. Specifically, as the total crime rate increases by 10% in time t-1, the demolition rate in time t decreases by 0.33%, on average. For the violent crime rate, a 10% increase in time t-1 coincides with a 1% decrease in demolitions in time t, on average. For property crime, a 10% increase in time t-1 is associated with a 0.4% decrease in demolitions in time t, on average. All results are statistically significant at the 5% level, giving strong indication that the relationship between the three crime categories and demolitions is indeed negative and non-zero.

| <b>Crime and Demolitions</b> |   |            |           |
|------------------------------|---|------------|-----------|
|                              | Dependent variable:<br>Rate of Demolition Permits |            |           |
|                              |   |            |           |
|                              | (1)   | (2)        | (3)       |
| Lag of Total Crime           | -0.033***   | :          |           |
|                              | (0.012)   |            |           |
| Lag of Violent Crime         |   | -0.096***  |           |
|                              |   | (0.032)    |           |
| Lag of Property Crime        |   |            | -0.040**  |
|                              |   |            | (0.017)   |
| Demographic Controls         | Yes   | Yes        | Yes       |
| Year Fixed Effects           | Yes   | Yes        | Yes       |
| CSA Fixed Effects            | Yes   | Yes        | Yes       |
| # of CSAs                    | 55  | 55         | 55        |
| Observations                 | 384   | 384        | 384       |
| R <sup>2</sup>               | 0.046   | 0.048      | 0.038     |
| Adjusted R <sup>2</sup>      | -0.183  | -0.180     | -0.192    |
| Note:                        | *p<0.1; *   | *p<0.05; * | ***p<0.01 |

 Table 3. Relationship between lagged crime and the prevalence of new demolition permits

 in a CSA

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at p<0.1, p<0.05, p<0.01. 384 observations are used from the full panel of 385 observations due to the one-year lag on crime. Results rendered with stargazer (Hlavac, 2022). Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

Demolitions are an important tool in Baltimore's arsenal for addressing vacant and abandoned properties, particularly those which are in such disrepair that they pose physical danger to residents (Cohen, 2001). Furthermore, vacancies are known to facilitate crime (Garvin et al., 2013), suggesting that their demolition may directly help in reducing crime and increasing the sense of order for neighborhood residents. However, I find that demolitions happen less often in areas with higher crime. In contrast to the results from my first model showing higher individual-level investment in higher crime areas, results from this model suggest that there is less municipal-level investment in higher crime areas. This is unfortunate, as these areas may need this investment the most.

It is important to compare the findings from the first and second models in relation to where these investments occur, and how they are used to facilitate physical order. Whereas rehabilitation projects occur in homes across a spectrum of conditions, demolitions are primarily used only for those homes which are no longer habitable. Thus, a higher rate of demolitions would be expected in areas with more uninhabitable homes. This is supported by the negative correlation between median price of homes sold and demolitions in Figure 2: given that the prevalence of uninhabitable homes drives down the value of homes nearby (Han, 2014), the negative correlation indicates that demolitions happen more frequently in areas with more uninhabitable homes.

My finding of a negative relationship between crime and demolitions, then, suggests that high crime neighborhoods are not experiencing the investment via demolitions from which they could substantially benefit. If these areas have more uninhabitable homes, and uninhabitable homes contribute to crime (Becker, 1968; Spader et al., 2016), the lack of demolitions may exacerbate the crime issue. In other words, these neighborhoods are not granted access to a potential mechanism that may pull them out of blight. This is an area for future improvement for Baltimore policymakers and city planners.

#### 6.4. Prevalence of Unoccupied Residential Properties

Table 4 shows that in areas with higher rates of total crime in the previous year (t-1), the share of unoccupied homes in the current year (t) is significantly higher. If the total crime rate increases by 10% in time t-1, then the rate of unoccupied homes increases by 0.1% in time t, on average. The sign of the trend is similarly positive for violent crime and property crime, with

violent crime associated with a larger increase in the rate of unoccupied homes. Specifically, if violent crime increases by 10% in time *t*-1, then the rate of unoccupied homes increases by 0.3% in time *t*, on average. If property crime increases 10% in time *t*-1, then the rate of unoccupied homes increases by 0.1% in time *t*, on average. All results are statistically significant at the 5% level, giving strong evidence that the relationship between crime and unoccupied homes is positive and non-zero.

 Table 4. Relationship between lagged crime and the prevalence of unoccupied homes in a CSA

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|                         | Dependent variable: Share of Unoccpuied Homes |            |          |
|-------------------------|---|------------|----------|
|                         |   |            |          |
|                         | (1)   | (2)        | (3)      |
| Lag of Total Crime      | 0.009***                                      |            |          |
|                         | (0.003)                                       |            |          |
| Lag of Violent Crime    |   | 0.030***   |          |
|                         |   | (0.009)    |          |
| Lag of Property Crime   |   |            | 0.011**  |
|                         |   |            | (0.005)  |
| Demographic Controls    | Yes   | Yes        | Yes      |
| Year Fixed Effects      | Yes   | Yes        | Yes      |
| CSA Fixed Effects       | Yes   | Yes        | Yes      |
| # of CSAs               | 55  | 55         | 55       |
| Observations            | 329   | 329        | 329      |
| R <sup>2</sup>          | 0.107   | 0.120      | 0.102    |
| Adjusted R <sup>2</sup> | -0.148  | -0.132     | -0.155   |
| Note:                   | *p<0.1; *                                     | *p<0.05; * | **p<0.01 |

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at p<0.1, p<0.05, p<0.01. 329 observations are used from the full panel of 330 observations due to the one-year lag on crime. Results rendered with stargazer (Hlavac, 2022). Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

In this model, I am looking at the relationship between crime and the rate of unoccupied homes, with the latter as a proxy for social disinvestment. My results show that neighborhoods with higher rates of crime have a higher share of unoccupied homes. This suggests that crime has a discouraging relationship with social and community investment in a neighborhood: higher crime areas may be seeing residents fleeing or may be struggling to attract new residents. This is troubling for the future of these neighborhoods in Baltimore's attempts to address crime and disorder, given that the literature strongly asserts that crime happens more in areas where there is less social cohesion and a lower sense of community (Shaw & McKay, 1942; Skogan, 1992; Sampson et al., 1997; Cancino, 2005; Iyer et al., 2020).

The choropleth maps show consistently high rates of non-occupancy in the same CSAs that have consistently high shares of black residents (Appendices F.6-F.7)— naïvely indicating that neighborhoods with more black residents have more unoccupied homes. Interestingly, though, the coefficient for the control variable on the share of black residents is negative and statistically significant (Appendix D.3), suggesting that holding the other controls for age, education, and poverty constant, areas with more black residents (relative to white residents, the reference group) actually have a lower rate of unoccupied homes. The result is statistically significant at the 1% level, indicating that with 99% confidence, the coefficient will not be zero. This provides strong confidence that the relationship is indeed inverse. Such a relationship is perplexing given the naïve picture portrayed in the map. Future studies of Baltimore should investigate how race may relate to rates of non-occupancy and disinvestment.

#### 6.5. Robustness Checks

In Appendices E.1-E.12, I perform a series of robustness checks, including testing for various time-lagged effects of crime, adding additional demographic controls, and including a

dummy variable to control for the COVID-19 pandemic in 2020 and 2021. The results of these alternate model specifications confirm that the original model specifications are appropriate. For example, the one-year crime lag is appropriate: significance disappears when I replace the lag on crime with crime in the current year for the relationship between crime and demolitions (Appendix E.5), and the relationship between total and property crime on non-occupancy (Appendix E.6); significance also disappears with the two-year lag structure on crime for the relationship to rehabilitation permits (Appendix E.7). These results affirm Lacoe et al.'s findings (2018), who demonstrate that a one-year lag on crime is the best method for demonstrating the relationship between crime and investment. Additionally, replacing the control for education with a continuous variable (log of median household income) resulted in similar coefficients.

#### 6.6. Limitations of the Study

#### 6.6.1. Crime Data

Crime statistics are officially reported by the Baltimore Police Department. However, crime data in general has its limitations. Reflecting just those incidents that are reported and properly logged by police officers, official crime statistics may deviate from perceptions of crime in a community (Buonanno et al., 2013). My model does not capture the differential relation to investment that reported crime may have versus perceived crime. This is a limitation of crime studies that is well documented and discussed (MacDonald, 2002; Gibbons, 2004; Tita et al. 2006; Buonanno et al., 2013). However, in lieu of having the capacity to track crime that goes unreported, this data serves as the most accessible measure of crime in Baltimore. Future research should seek to isolate this difference, perhaps by using victimization data rather than reported crime rates, as per Buonanno et al. (2013).

## 6.6.2. Size of CSAs

CSAs are larger than census tracts and neighborhoods— they consist of 1-8 tracts and have populations of up to 20,000 people (Appendix A). Accordingly, a crime that happens on one side of a CSA may not significantly impact residents living at the other end. Future studies of Baltimore may investigate this potential limitation by matching the housing indicator data to the corresponding census tracts and running the same models to see if the relationship between crime and investment changes at a more granular geographic level.

That being said, some CSAs only have a few census tracts (Appendix B). Therefore, the differences between the units may not be large enough to result in significantly different findings.

## 6.6.3. Availability of Data

Data on community vital signs is only available from 2015 to 2021. With more data, results and conclusions may be more robust. On the other hand, though, including more data would necessitate controls for events such as the Great Recession of 2007-2009, in which employment in urban areas did not return to pre-recession employment levels until 2014 (Hertz et al., 2014). The Great Recession and its aftermath may have differentially impacted families and the indicators relevant to their housing investment, with high rates of unemployment limiting a household's disposable income that may be used for rehabilitation projects. These events may compromise models that use data from these periods, which supports the use of data that is removed from these events.

#### 6.6.4. Crime Displacement

Though rehabilitation projects and investment in properties are promising for their relationship with lower crime rates (Spader et al., 2016; Kuhlmann, 2020; South et al., 2023),

there is a limitation of this approach for reducing crime in totality. There is the possibility that crime does not decrease overall, but merely shifts locations (i.e. the crime is "displaced"). In 1999, Schumacher and Leitner used a hot spot analysis to test if this occurs in Baltimore, by looking at whether urban renewal programs in Baltimore have affected the spatial distribution of crime. They find that despite some projects significantly discouraging criminal activity in certain areas, overall crime in the city remained constant. They conclude, then, that those projects did not eliminate criminal activity—they merely displaced it.

I recommend that future research investigate the possibility of displacement as it relates to the current crime prevention policies in Baltimore. However, given that my choropleth maps (Appendices F.1 - F.3) do not show an obvious displacement effect, this may not be an urgent issue.

#### 7. Conclusions, Implications, and Policy Recommendations

#### 7.1. Conclusions

In this study, I ask: how does crime relate to investment and disinvestment in residential properties in Baltimore? The answer to this question may indicate whether Baltimore neighborhoods are able to respond to higher rates of crime in ways that may break a "spiral of decay." To model the relationship in question, I used crime and housing indicator data for an OLS regression with two-way fixed effects that control for variation across time and space, and I included additional controls for socioeconomic characteristics. Overall, I found that both investment and disinvestment are related to higher rates of crime in Baltimore, suggesting that areas with higher crime may simultaneously experience improvements in aspects of physical and social order, while simultaneously worsening in other aspects of physical and social order.

Specifically, individual investment via rehabilitation projects increases along with crime, but municipal investment via demolitions decreases with crime, and community disinvestment via non-occupancy increases with crime. My findings affirm the arguments advanced by existing literature which assert that crime is strongly related to indicators of physical and social disorder, while offering a novel perspective on how crime relates to actions which may *change* conditions of physical and social disorder. Thus, my results suggest that city officials should consider neighborhood-level crime rates when crafting and evaluating policies for improving residential conditions in Baltimore, with a focus on increasing the types of investments that are currently underutilized in higher crime areas.

## 7.2. Implications and Policy Recommendations

In 2020, Baltimore elected Brandon Scott as mayor, and his administration has since implemented significant plans for policing reforms and strategies to mitigate the vacancy crisis and its negative spillover effects for Baltimoreans. Below, I offer some recommendations for how these policies should be evaluated given my findings of a significant positive relationship between crime and resident investment, a significant negative relationship between crime and municipal investment, and a significant positive relationship between crime and community disinvestment.

#### 7.2.1. Evaluating Crime Prevention Policies

Crime prevention, according to Herbert and Harries (1986), "is less concerned with the search for offenders than with creating conditions in which offenses are less likely to occur" (p. 281). Baltimore, however, has a troubling history with crime prevention and policing, one which forced the Department of Justice to intervene in 2017 with a Consent Decree to commit Baltimore to remedying its practices of unconstitutional policing (*City of Baltimore Consent* 

*Decree*, n.d.). Many reforms have been implemented since then. For example, a 2021 plan from Scott's administration expands opportunities for community engagement. These approaches aim to change the focus of policing: from fighting crime to *preventing* crime, by working with the community to address issues of safety and trust in law enforcement (*Baltimore City Comprehensive Violence Prevention Plan*, 2021). Given my findings that there is less community investment in high-crime areas between 2015 and 2021, it will be interesting to see if Scott's policing plan can induce more community cohesion and invite more residential housing occupancy into these higher-crime neighborhoods. If this is the case, this would be a promising result not just for Baltimore, but for potential applications to other cities with high-crime rates.

Along with increased community cohesion, Baltimore should recognize the potential of infrastructure and area-based policies to impact crime levels and the health of their housing market. If demolitions are not happening in higher crime areas, as my findings show, then this likely contributes to a spiral of worsening housing conditions, which begets more crime. Thus, Baltimore should consider increasing its capacity for demolitions, especially in high-crime neighborhoods.<sup>20</sup>

### 7.2.2. Evaluating Housing Development Policies

Good housing quality has positive spillovers into many other aspects of a person's life. Frieden (1968) argues that housing policy should facilitate this positive spillover by providing citizens with the freedom of residential choice. In other words, giving citizens access to quality housing will in turn provide access to good schools, adequate public services, and job

<sup>&</sup>lt;sup>20</sup> It is worth noting that recent debates about housing development have brought up the importance of environmental sustainability, especially as it relates to compact redevelopment (Mueller & Steiner, 2010). While important issues, they extend beyond the reach of this paper. As such, I encourage future research to consider the impact of crime rates and crime policies on the uptake of environmentally sustainable manners for home rehabilitation projects and demolitions.

opportunities. Baltimore has recently enacted some policies to provide this sort of access and choice to its residents.

In 2022, Mayor Brandon Scott directed \$39 million from federal COVID-19 relief funds to address the crisis of vacant homes plaguing his city (Miller & Little, 2022). Perhaps unsurprisingly, these funds address metrics that have clear and direct relationships with the housing supply. Specifically, the funds are allocated for building and bulldozing, upgrades to the city's permitting system, housing enhancements for legacy residents, and more pathways for renters to become homeowners (ibid).

However, considering the high crime rates in areas with a significant number of unoccupied homes, Baltimore may consider implementing initiatives that focus on engaging residents in their local communities. For example, Baltimore residents recently expressed interest in expanding youth programs and supporting small, local businesses as a way to reduce crime (Cantora et al., 2016); thus, the city may consider starting with such programs. Additionally, to ensure the reliability of the data as a proxy for community investment/disinvestment, city officials may consider investigating why homes in high-crime areas frequently fail to receive mail. Finding new and innovative ways to encourage people to stay in their homes and engage with their neighbors may foster stronger, more resilient communities.

In its policy evaluations, Baltimore should consider both the direct and indirect effects of crime on housing and community investment. This approach may be effective for crime prevention strategies and for fostering social cohesion, providing a possible path to guide urban communities out of blight. As this Rust Belt city continues to evaluate its policies, the results from this research may serve as a framework for discussions on crime reduction, community

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resilience, and urban renewal, providing a potential framework for other cities to soon implement.

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## Appendices

## **Appendix A: Community Statistical Areas**

The Baltimore Neighborhood Indicators Alliance Jacob France Institute (BNIA-JFI) uses

Community Statistical Areas (CSAs) to consolidate data on over 270 neighborhoods in

Baltimore. Neighborhoods are small areas combining social and geographic aspects, but the

boundaries defined by the city can differ from those understood by residents. Alternatively,

CSAs are consistent boundaries, allowing more accurate comparisons of conditions over time.

CSAs were originally developed by the Baltimore Data Collaborative with the Baltimore

City Department of Planning, using four guidelines:

- 1. CSA boundaries had to align with Census Tracts;
- 2. CSAs would consist of 1-8 tracts, preferably with total populations in the range of 5,000 to 20,000;
- 3. CSAs would define relatively demographically homogeneous areas;
- 4. CSAs should reflect the City planners' understanding of residents' and institutions' perceptions of the boundaries of the community (*BNIA Mapping Resources*, n.d.)

With the results of the decennial census, census tract definitions may change. Accordingly,

BNIA-JFI may re-evaluate the CSA boundaries. Given the results of the 2020 census, however,

BNIA-JFI decided to maintain the existing CSA boundaries, only changing the names of some

areas at the request of community members. Thus, my unit of analysis remained constant from

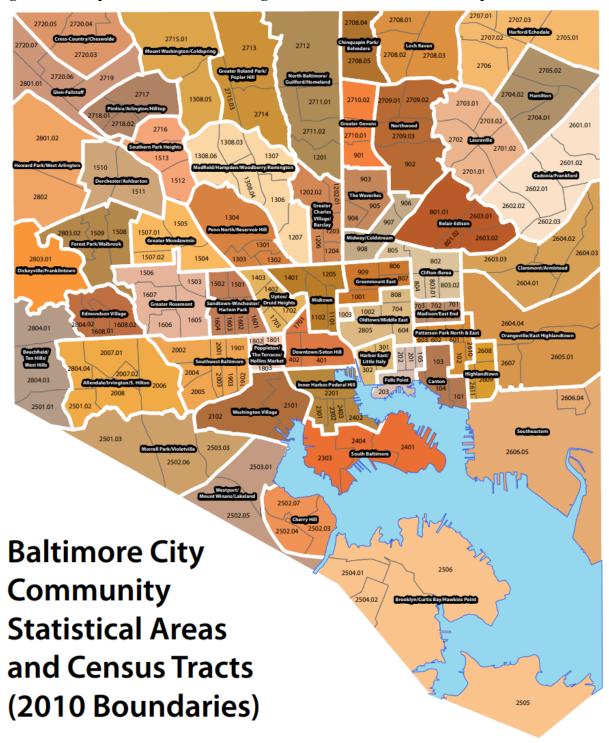
pre-2020 to post-2020.

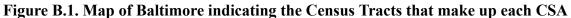




Source: Baltimore City Health Department.

# Appendix B: Map of Baltimore CSAs and Census Tracts





Source: Baltimore Neighborhood Indicators Alliance (2020)

## **Appendix C: Modifications of Variables in the Data**

### C.1. Formula for adjusting prices to 2021 dollars

Current value = Original value 
$$\times \left(\frac{Current CPI}{CPI in the past}\right)$$
.

Source: St. Louis Fed, https://research.stlouisfed.org/publications/page1-econ/2023/01/03/adjusting-for-inflation

### C.2. Real Median Household Income

C.3. Real Median Price of Homes Sold

## **Appendix D: Regression Outputs**

|                         | Dependent variable:         |            |             |
|-------------------------|-----------------------------|------------|-------------|
|                         | Rate of Rehabilitation Pern |            |             |
|                         | (1)                         | (2)        | (3)         |
| Lag of Total Crime      | 0.008**                     |            |             |
| -                       | (0.003)                     |            |             |
| Lag of Violent Crime    |                             | 0.021**    |             |
|                         |                             | (0.010)    |             |
| Lag of Property Crime   | ;                           |            | $0.010^{*}$ |
|                         |                             |            | (0.005)     |
| Black                   | -0.100***                   | -0.096***  | -0.103**    |
|                         | (0.034)                     | (0.034)    | (0.034)     |
| Asian                   | -0.119                      | -0.119     | -0.102      |
|                         | (0.075)                     | (0.074)    | (0.075)     |
| Hispanic                | -0.062*                     | -0.059*    | -0.063*     |
|                         | (0.034)                     | (0.034)    | (0.034)     |
| Two or more races       | -0.047                      | -0.057     | -0.047      |
| Two of more fuees       | (0.090)                     | (0.089)    | (0.090)     |
| All other races         | -0.443***                   | -0.424***  | -0.430**    |
|                         | (0.141)                     | (0.140)    | (0.141)     |
| Under 5 years           | -0.078                      | -0.075     | -0.079      |
|                         | (0.075)                     | (0.074)    | (0.075)     |
| 5-17 years              | 0.012                       | 0.011      | 0.013       |
|                         | (0.070)                     | (0.069)    | (0.070)     |
| 18-24 years             | -0.089                      | -0.087     | -0.089      |
| -                       | (0.072)                     | (0.072)    | (0.073)     |
| 25-64 years             | -0.043                      | -0.038     | -0.041      |
|                         | (0.057)                     | (0.057)    | (0.058)     |
| HS and some College     | 0.032                       | 0.031      | 0.032       |
|                         | (0.041)                     | (0.041)    | (0.041)     |
| Bachelor's or more      | -0.003                      | -0.00002   | -0.003      |
|                         | (0.043)                     | (0.043)    | (0.043)     |
| Employed                | 0.027                       | 0.030      | 0.025       |
|                         | (0.030)                     | (0.029)    | (0.030)     |
| Below Poverty           | -0.011                      |            | -0.012      |
|                         | (0.030)                     |            | (0.030)     |
| Year Fixed Effects      | Yes                         | Yes        | Yes         |
| CSA Fixed Effects       | Yes                         | Yes        | Yes         |
| # of CSAs               | 55                          | 55         | 55          |
| Observations            | 384                         | 384        | 384         |
| R <sup>2</sup>          | 0.087                       | 0.083      | 0.081       |
| Adjusted R <sup>2</sup> | -0.131                      | -0.133     | -0.140      |
| Note:                   | *n<0.1·                     | ***p<0.05; | ****p<0.0   |

## **D.1.** Crime and Rehabilitation Permits, expanded control variables

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. 384 observations are used from the full panel of 385 observations due to the one-year lag on crime. Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

| Full OLS Regression Results: Demolitions |                     |            | itions   |
|--|---------------------|------------|----------|
|  | Dependent variable: |            |          |
|  | Rate of I           | Demolitior | Permits  |
|  | (1)                 | (2)        | (3)      |
| Lag of Total Crime                       | -0.033***           |            |          |
| -  | (0.012)             |            |          |
| Lag of Violent Crime                     |                     | -0.096***  | :        |
| 5  |                     | (0.032)    |          |
| Lag of Property Crime                    |                     |            | -0.040** |
| Lug of Hoporty office                    | ,<br>,              |            | (0.017)  |
| Black                                    | 0.073               | 0.056      | 0.085    |
| Didek                                    | (0.114)             | (0.113)    | (0.115)  |
| Asian                                    | 0.256               | 0.268      | 0.196    |
| Asiali                                   | (0.253)             | (0.253)    | (0.251)  |
| Uismania                                 | 0.027               | 0.013      | 0.031    |
| Hispanic                                 | (0.115)             | (0.114)    | (0.116)  |
| T  |                     |            | . ,      |
| Two or more races                        | -0.362              | -0.327     | -0.359   |
|  | (0.302)             | (0.302)    | (0.303)  |
| All other races                          | 0.396               | 0.335      | 0.343    |
|  | (0.473)             | (0.472)    | (0.475)  |
| Under 5 years                            | -0.213              | -0.233     | -0.206   |
|  | (0.252)             | (0.251)    | (0.254)  |
| 5-17 years                               | 0.063               | 0.060      | 0.060    |
|  | (0.234)             | (0.234)    | (0.235)  |
| 18-24 years                              | -0.023              | -0.026     | -0.022   |
|  | (0.244)             | (0.243)    | (0.245)  |
| 25-64 years                              | -0.025              | -0.039     | -0.030   |
| -  | (0.193)             | (0.193)    | (0.194)  |
| HS and some College                      | -0.116              | -0.101     | -0.115   |
|  | (0.138)             | (0.138)    | (0.139)  |
| Bachelor's or more                       | -0.008              | -0.011     | -0.004   |
|  | (0.146)             | (0.146)    | (0.147)  |
| Employed                                 | -0.027              | -0.031     | -0.020   |
|  | (0.101)             | (0.100)    | (0.101)  |
| Below Poverty                            | 0.036               | 0.029      | 0.041    |
| ,  | (0.100)             | (0.100)    | (0.100)  |
| Year Fixed Effects                       | Yes                 | Yes        | Yes      |
| CSA Fixed Effects                        | Yes                 | Yes        | Yes      |
| # of CSAs                                | 55                  | 55         | 55       |
| Observations                             | 384                 | 384        | 384      |
| R <sup>2</sup>                           | 0.046               | 0.048      | 0.038    |
| Adjusted R <sup>2</sup>                  | -0.183              | -0.180     | -0.192   |
|  |                     |            |          |
| Note:                                    | p<0.1;              | *p<0.05; * | p<0.01   |

# **D.2.** Crime and Demolition Permits, expanded control variables

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. 384 observations are used from the full panel of 385 observations due to the one-year lag on crime. Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

|                         | Dependent variable: |               |             |
|-------------------------|---------------------|---------------|-------------|
|                         |                     |               |             |
|                         | (1)                 | (2)           | (3)         |
| Lag of Total Crime      | 0.009***            |               |             |
| 0                       | (0.003)             |               |             |
| Lag of Violent Crime    |                     | 0.030***      |             |
| C                       |                     | (0.009)       |             |
| Lag of Property Crime   |                     |               | 0.011**     |
|                         |                     |               | (0.005)     |
| Black                   | -0.101***           | -0.096***     | -0.105**    |
|                         | (0.037)             | (0.036)       | (0.037)     |
| Asian                   | 0.005               | -0.007        | 0.020       |
|                         | (0.077)             | (0.077)       | (0.077)     |
| Hispanic                | -0.058              | -0.054        | -0.061      |
| 1                       | (0.035)             | (0.035)       | (0.036)     |
| Two or more races       | -0.101              | -0.112        | -0.103      |
|                         | (0.113)             | (0.112)       | (0.113)     |
| All other races         | -0.202              | -0.190        | -0.186      |
|                         | (0.149)             | (0.148)       | (0.150)     |
| Under 5 years           | 0.008               | 0.011         | 0.004       |
|                         | (0.083)             | (0.082)       | (0.083)     |
| 5-17 years              | 0.056               | 0.054         | 0.057       |
|                         | (0.074)             | (0.073)       | (0.074)     |
| 18-24 years             | 0.043               | 0.046         | 0.042       |
|                         | (0.075)             | (0.075)       | (0.075)     |
| 25-64 years             | -0.011              | -0.009        | -0.009      |
|                         | (0.060)             | (0.059)       | (0.060)     |
| HS and some College     | -0.041              | -0.046        | -0.040      |
|                         | (0.044)             | (0.044)       | (0.044)     |
| Bachelor's or more      | -0.088*             | -0.091*       | -0.087      |
|                         | (0.047)             | (0.046)       | (0.047)     |
| Employed                | -0.023              | -0.023        | -0.025      |
|                         | (0.032)             | (0.032)       | (0.033)     |
| Below Poverty           | $0.075^{**}$        | $0.077^{***}$ | $0.075^{*}$ |
|                         | (0.030)             | (0.029)       | (0.030)     |
| Year Fixed Effects      | Yes                 | Yes           | Yes         |
| CSA Fixed Effects       | Yes                 | Yes           | Yes         |
| # of CSAs               | 55                  | 55            | 55          |
| Observations            | 329                 | 329           | 329         |
| R <sup>2</sup>          | 0.107               | 0.120         | 0.102       |
| Adjusted R <sup>2</sup> |                     | -0.132        | -0.155      |

## D.3. Crime and Non-Occupancy Rates, expanded control variables

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. 329 observations are used from the full panel of 330 observations due to the one-year lag on crime. Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

## **Appendix E: Robustness Checks**

The robustness checks in the following sections include: adding a COVID-19 dummy variable for years 2020 and 2021, using explanatory variables of interest in the current time period instead of the one-year lagged period, using explanatory variables of interest in the two year-lagged time period instead of the one-year lagged period, and replacing the shares of the population by educational attainment with the log of real median household income (in 2021\$) as a continuous variable.

## E.1. Including a COVID Dummy; Results for Rehabilitation Permits on 1-year Crime Lag

|                         | Depe                           | ndent vari | able:       |  |
|-------------------------|--------------------------------|------------|-------------|--|
|                         | Rate of Rehabilitation Permits |            |             |  |
|                         | (1)                            | (2)        | (3)         |  |
| Lag of Total Crime      | 0.008**                        |            |             |  |
|                         | (0.003)                        |            |             |  |
| Lag of Violent Crime    |                                | 0.021**    |             |  |
|                         |                                | (0.010)    |             |  |
| Lag of Property Crime   |                                |            | $0.010^{*}$ |  |
|                         |                                |            | (0.005)     |  |
| Demographic Controls    | Yes                            | Yes        | Yes         |  |
| COVID Dummy             | Yes                            | Yes        | Yes         |  |
| Year Fixed Effects      | Yes                            | Yes        | Yes         |  |
| CSA Fixed Effects       | Yes                            | Yes        | Yes         |  |
| # of CSAs               | 55                             | 55         | 55          |  |
| Observations            | 384                            | 384        | 384         |  |
| R <sup>2</sup>          | 0.084                          | 0.081      | 0.077       |  |
| Adjusted R <sup>2</sup> | -0.132                         | -0.136     | -0.141      |  |
| Note:                   | *p<0.1;                        | **p<0.05;  | ****p<0.01  |  |

**Crime and Rehabilitation Permits** 

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. 384 observations are used from the full panel of 385 observations due to the one-year lag on crime. Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

#### E.2. Including a COVID Dummy; Results for Demolition Permits on 1-year Crime Lag

|                         | Dependent variable:        |             |          |  |  |
|-------------------------|----------------------------|-------------|----------|--|--|
|                         | Rate of Demolition Permits |             |          |  |  |
|                         | (1)                        | (2)         | (3)      |  |  |
| Lag of Total Crime      | -0.031***                  | ¢           |          |  |  |
|                         | (0.011)                    |             |          |  |  |
| Lag of Violent Crime    |                            | -0.090***   |          |  |  |
|                         |                            | (0.032)     |          |  |  |
| Lag of Property Crime   |                            |             | -0.036** |  |  |
|                         |                            |             | (0.017)  |  |  |
| Demographic Controls    | Yes                        | Yes         | Yes      |  |  |
| COVID Dummy             | Yes                        | Yes         | Yes      |  |  |
| Year Fixed Effects      | Yes                        | Yes         | Yes      |  |  |
| CSA Fixed Effects       | Yes                        | Yes         | Yes      |  |  |
| # of CSAs               | 55                         | 55          | 55       |  |  |
| Observations            | 384                        | 384         | 384      |  |  |
| R <sup>2</sup>          | 0.082                      | 0.085       | 0.075    |  |  |
| Adjusted R <sup>2</sup> | -0.134                     | -0.131      | -0.142   |  |  |
| Note:                   | *n<0.1.*                   | **p<0.05; * | **n<0.01 |  |  |

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. 384 observations are used from the full panel of 385 observations due to the one-year lag on crime. Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

| Crime and Non-Occupancy |                          |            |          |  |
|-------------------------|--------------------------|------------|----------|--|
|                         | Dependent variable:      |            |          |  |
|                         | Share of Unoccpuied Home |            |          |  |
|                         | (1)                      | (2)        | (3)      |  |
| Lag of Total Crime      | 0.009***                 |            |          |  |
|                         | (0.003)                  |            |          |  |
| Lag of Violent Crime    |                          | 0.030***   |          |  |
|                         |                          | (0.009)    |          |  |
| Lag of Property Crime   |                          |            | 0.011**  |  |
|                         |                          |            | (0.005)  |  |
| Demographic Controls    | Yes                      | Yes        | Yes      |  |
| COVID Dummy             | Yes                      | Yes        | Yes      |  |
| Year Fixed Effects      | Yes                      | Yes        | Yes      |  |
| CSA Fixed Effects       | Yes                      | Yes        | Yes      |  |
| # of CSAs               | 55                       | 55         | 55       |  |
| Observations            | 329                      | 329        | 329      |  |
| R <sup>2</sup>          | 0.094                    | 0.106      | 0.089    |  |
| Adjusted R <sup>2</sup> | -0.161                   | -0.145     | -0.167   |  |
| Note:                   | *p<0.1; *                | *p<0.05; * | **p<0.01 |  |

E.3. Including a COVID Dummy; Results for Share of Unoccupied Homes on 1-year Crime Lag

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. 329 observations are used from the full panel of 330 observations due to the one-year lag on crime. Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

| Crime and Rehabilitation Permits |                     |                               |            |  |  |
|----------------------------------|---------------------|-------------------------------|------------|--|--|
|                                  | Dependent variable: |                               |            |  |  |
|                                  | Rate of R           | Rate of Rehabilitation Permit |            |  |  |
|                                  | (1)                 | (2)                           | (3)        |  |  |
| Total Crime                      | 0.028***            |                               |            |  |  |
|                                  | (0.006)             |                               |            |  |  |
| Violent Crime                    |                     | 0.074***                      |            |  |  |
|                                  |                     | (0.016)                       |            |  |  |
| Property Crime                   |                     |                               | 0.030***   |  |  |
|                                  |                     |                               | (0.007)    |  |  |
| Demographic Controls             | Yes                 | Yes                           | Yes        |  |  |
| Year Fixed Effects               | Yes                 | Yes                           | Yes        |  |  |
| CSA Fixed Effects                | Yes                 | Yes                           | Yes        |  |  |
| # of CSAs                        | 55                  | 55                            | 55         |  |  |
| Observations                     | 385                 | 385                           | 385        |  |  |
| R <sup>2</sup>                   | 0.141               | 0.126                         | 0.120      |  |  |
| Adjusted R <sup>2</sup>          | -0.065              | -0.083                        | -0.090     |  |  |
| Note:                            | *p<0.1;             | ***p<0.05;                    | ****p<0.01 |  |  |

#### E.4. Using Crime Rate in Current Period; Results for Rehabilitation Permits

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

|                         | Dependent variable:        |            |         |  |
|-------------------------|----------------------------|------------|---------|--|
|                         | Rate of Demolition Permits |            |         |  |
|                         | (1)                        | (2)        | (3)     |  |
| Total Crime             | -0.013                     |            |         |  |
|                         | (0.020)                    |            |         |  |
| Violent Crime           |                            | -0.097*    |         |  |
|                         |                            | (0.057)    |         |  |
| Property Crime          |                            |            | -0.012  |  |
|                         |                            |            | (0.024) |  |
| Demographic Controls    | Yes                        | Yes        | Yes     |  |
| Year Fixed Effects      | Yes                        | Yes        | Yes     |  |
| CSA Fixed Effects       | Yes                        | Yes        | Yes     |  |
| # of CSAs               | 55                         | 55         | 55      |  |
| Observations            | 385                        | 385        | 385     |  |
| R <sup>2</sup>          | 0.022                      | 0.030      | 0.022   |  |
| Adjusted R <sup>2</sup> | -0.211                     | -0.202     | -0.212  |  |
| Note:                   | * *                        | *p<0.05; * | ***     |  |

#### E.5. Using Crime Rate in Current Period; Results for Demolition Permits

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

|                         | Dependent variable:      |            |          |  |
|-------------------------|--------------------------|------------|----------|--|
|                         | Share of Unoccpuied Home |            |          |  |
|                         | (1)                      | (2)        | (3)      |  |
| Total Crime             | 0.007                    |            |          |  |
|                         | (0.006)                  |            |          |  |
| Violent Crime           |                          | 0.037**    |          |  |
|                         |                          | (0.018)    |          |  |
| Property Crime          |                          |            | 0.004    |  |
|                         |                          |            | (0.007)  |  |
| Demographic Controls    | Yes                      | Yes        | Yes      |  |
| Year Fixed Effects      | Yes                      | Yes        | Yes      |  |
| CSA Fixed Effects       | Yes                      | Yes        | Yes      |  |
| # of CSAs               | 55                       | 55         | 55       |  |
| Observations            | 330                      | 330        | 330      |  |
| R <sup>2</sup>          | 0.086                    | 0.097      | 0.083    |  |
| Adjusted R <sup>2</sup> | -0.175                   | -0.160     | -0.179   |  |
| Note:                   | * *                      | *p<0.05; * | *** 0.01 |  |

#### E.6. Using Crime Rate in Current Period; Results for Share of Unoccupied Homes

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

| <b>Crime and Rehabilitation Permits</b> |  |         |         |  |
|---|--|---------|---------|--|
|   | Dependent variable:<br>Rate of Rehabilitation Perm |         |         |  |
|   |  |         |         |  |
|   | (1)  | (2)     | (3)     |  |
| 2-Year Lag, Total Crime                 | 0.0004   |         |         |  |
|   | (0.003)  |         |         |  |
| 2-Year Lag, Violent Crime               |  | 0.001   |         |  |
|   |  | (0.008) |         |  |
| 2-Year Lag, Property Crime              |  |         | -0.003  |  |
|   |  |         | (0.005) |  |
| Demographic Controls                    | Yes  | Yes     | Yes     |  |
| Year Fixed Effects                      | Yes  | Yes     | Yes     |  |
| CSA Fixed Effects                       | Yes  | Yes     | Yes     |  |
| # of CSAs                               | 55   | 55      | 55      |  |
| Observations                            | 383  | 383     | 383     |  |
| R <sup>2</sup>                          | 0.070  | 0.070   | 0.071   |  |
| Adjusted R <sup>2</sup>                 | -0.154   | -0.154  | -0.153  |  |

### E.7. Using a 2-year Lagged Crime Rate; Results for Rehabilitation Permits

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. 383 observations are used from the full panel of 385 observations due to the two-year lag on crime. Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

| E.8. Using a 2-year Lagged Crime Rate; Results for Demolition Permits |
|---|
|   |

|                            | Dependent variable:Rate of Demolition Permit |            |            |  |
|----------------------------|--|------------|------------|--|
|                            |  |            |            |  |
|                            | (1)  | (2)        | (3)        |  |
| 2-Year Lag, Total Crime    | -0.036***                                    |            |            |  |
|                            | (0.010)                                      |            |            |  |
| 2-Year Lag, Violent Crime  |  | -0.100***  |            |  |
|                            |  | (0.027)    |            |  |
| 2-Year Lag, Property Crime |  |            | -0.051***  |  |
|                            |  |            | (0.015)    |  |
| Demographic Controls       | Yes  | Yes        | Yes        |  |
| Year Fixed Effects         | Yes  | Yes        | Yes        |  |
| CSA Fixed Effects          | Yes  | Yes        | Yes        |  |
| # of CSAs                  | 55   | 55         | 55         |  |
| Observations               | 383  | 383        | 383        |  |
| R <sup>2</sup>             | 0.062  | 0.062      | 0.056      |  |
| Adjusted R <sup>2</sup>    | -0.164                                       | -0.163     | -0.171     |  |
| Note:                      | *p<0.1;                                      | ***p<0.05; | ****p<0.01 |  |

#### **Crime and Demolition Permits**

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. 383 observations are used from the full panel of 385 observations due to the two-year lag on crime. Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

| Crime and N                | lon-Occuj               | pancy      |           |
|----------------------------|-------------------------|------------|-----------|
|                            | Depe                    | endent var | iable:    |
|                            | Share of Unoccupied Hom |            |           |
|                            | (1)                     | (2)        | (3)       |
| 2-Year Lag, Total Crime    | -0.036***               |            |           |
|                            | (0.010)                 |            |           |
| 2-Year Lag, Violent Crime  |                         | -0.100***  | <b>:</b>  |
|                            |                         | (0.027)    |           |
| 2-Year Lag, Property Crime |                         |            | -0.051*** |
|                            |                         |            | (0.015)   |
| Demographic Controls       | Yes                     | Yes        | Yes       |
| Year Fixed Effects         | Yes                     | Yes        | Yes       |
| CSA Fixed Effects          | Yes                     | Yes        | Yes       |
| # of CSAs                  | 55                      | 55         | 55        |
| Observations               | 383                     | 383        | 383       |
| R <sup>2</sup>             | 0.062                   | 0.062      | 0.056     |
| Adjusted R <sup>2</sup>    | -0.164                  | -0.163     | -0.171    |

#### E.9. Using a 2-year Lagged Crime Rate; Results for Share of Unoccupied Homes

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. 383 observations are used from the full panel of 385 observations due to the two-year lag on crime. Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

|                                | Dependent variable:           Rate of Rehabilitation Perm |           |             |
|--------------------------------|---|-----------|-------------|
|                                |   |           |             |
|                                | (1)   | (2)       | (3)         |
| Lag of Total Crime             | 0.008**   |           |             |
|                                | (0.003)   |           |             |
| Lag of Violent Crime           |   | 0.021**   |             |
|                                |   | (0.010)   |             |
| Lag of Property Crime          |   |           | $0.010^{*}$ |
|                                |   |           | (0.005)     |
| Demographic Controls           | Yes   | Yes       | Yes         |
| Log of Median Household Income | Yes   | Yes       | Yes         |
| Year Fixed Effects             | Yes   | Yes       | Yes         |
| CSA Fixed Effects              | Yes   | Yes       | Yes         |
| # of CSAs                      | 55  | 55        | 55          |
| Observations                   | 384   | 384       | 384         |
| R <sup>2</sup>                 | 0.084   | 0.081     | 0.077       |
| Adjusted R <sup>2</sup>        | -0.132  | -0.136    | -0.141      |
| Note:                          | *n<0.1:   | **p<0.05; | ***p<0.01   |

# E.10. Replacing Education Controls with Median Household Income Control; Results for Rehabilitation Permits

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at \* p<0.1, \*\* p<0.05, \*\*\* p<0.01.384 observations are used from the full panel of 385 observations due to the one-year lag on crime. Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

| <b>Crime and Demolition Permits</b> |                          |            |           |  |
|-------------------------------------|--------------------------|------------|-----------|--|
|                                     | Dependent variable:      |            |           |  |
|                                     | Rate of Demolition Permi |            |           |  |
|                                     | (1)                      | (2)        | (3)       |  |
| Lag of Total Crime                  | -0.031***                |            |           |  |
|                                     | (0.011)                  |            |           |  |
| Lag of Violent Crime                |                          | -0.090***  |           |  |
|                                     |                          | (0.032)    |           |  |
| Lag of Property Crime               |                          |            | -0.036**  |  |
|                                     |                          |            | (0.017)   |  |
| Demographic Controls                | Yes                      | Yes        | Yes       |  |
| Log of Median Household Income      | Yes                      | Yes        | Yes       |  |
| Year Fixed Effects                  | Yes                      | Yes        | Yes       |  |
| CSA Fixed Effects                   | Yes                      | Yes        | Yes       |  |
| # of CSAs                           | 55                       | 55         | 55        |  |
| Observations                        | 384                      | 384        | 384       |  |
| R <sup>2</sup>                      | 0.082                    | 0.085      | 0.075     |  |
| Adjusted R <sup>2</sup>             | -0.134                   | -0.131     | -0.142    |  |
| Note:                               | *p<0.1; *                | *p<0.05; * | ***p<0.01 |  |

## E.11. Replacing Education Controls with Median Household Income Control; Results for Demolition Permits

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. 384 observations are used from the full panel of 385 observations due to the one-year lag on crime. Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

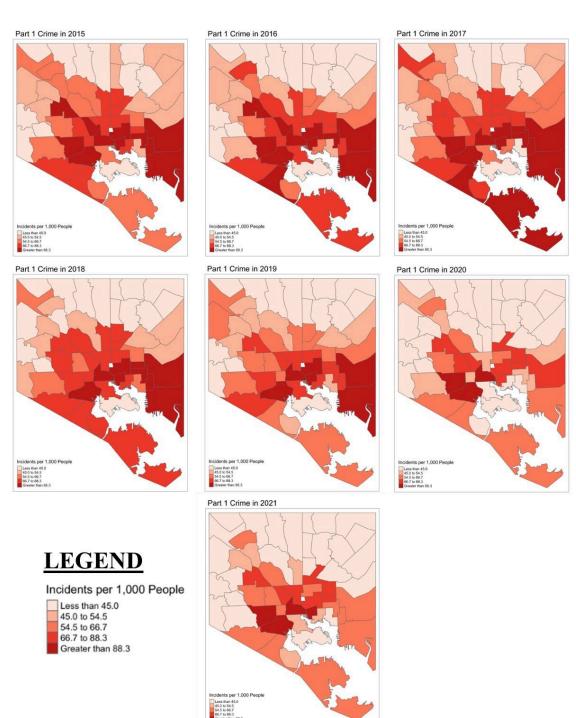
| Crime and Non-Occupancy        |  |            |          |
|--------------------------------|--|------------|----------|
|                                | Dependent variable:<br>Share of Unoccupied Homes |            |          |
|                                |  |            |          |
|                                | (1)  | (2)        | (3)      |
| Lag of Total Crime             | 0.009***   |            |          |
|                                | (0.003)  |            |          |
| Lag of Violent Crime           |  | 0.030***   |          |
|                                |  | (0.009)    |          |
| Lag of Property Crime          |  |            | 0.011**  |
|                                |  |            | (0.005)  |
| Demographic Controls           | Yes  | Yes        | Yes      |
| Log of Median Household Income | Yes  | Yes        | Yes      |
| Year Fixed Effects             | Yes  | Yes        | Yes      |
| CSA Fixed Effects              | Yes  | Yes        | Yes      |
| # of CSAs                      | 55   | 55         | 55       |
| Observations                   | 329  | 329        | 329      |
| <b>R</b> <sup>2</sup>          | 0.094  | 0.106      | 0.089    |
| Adjusted R <sup>2</sup>        | -0.161   | -0.145     | -0.167   |
| Note:                          | *p<0.1; **                                       | *p<0.05; * | **p<0.01 |

## E.12. Replacing Education Controls with Median Household Income Control; Results for Share of Unoccupied Homes

Notes: Standard errors are in parentheses. Levels of statistical significance are indicated at \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. 329 observations are used from the full panel of 330 observations due to the one-year lag on crime. Source: Author's calculations using Baltimore Department of Housing and Community Development, Baltimore Police Department, and US Census American Community Survey data, 2015-2021.

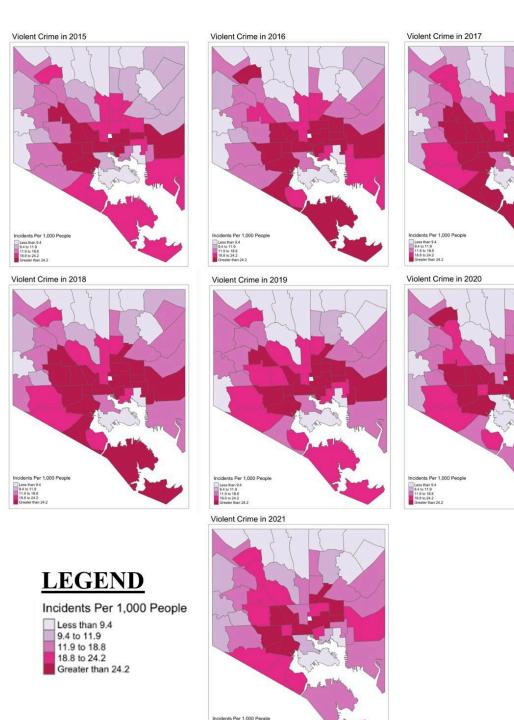
#### **Appendix F: Maps**

#### F.1. Total Part 1 Crime Rates



**APPENDIX F.1: TOTAL CRIME RATES** 

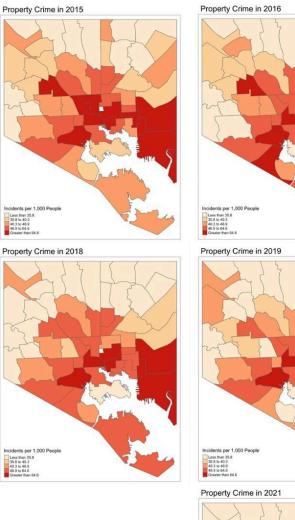
Source: Author's calculations using Baltimore Police Department data, 2015-2021.



## **APPENDIX F.2: VIOLENT CRIME RATES**

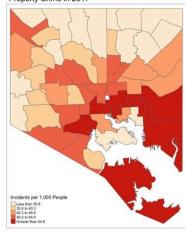
Source: Author's calculations using Baltimore Police Department data, 2015-2021.

to 11.9 to 18.8 to 24.2

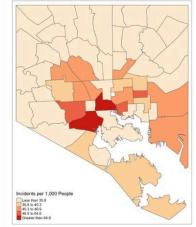


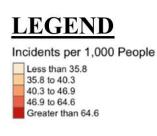
## **APPENDIX F.3: PROPERTY CRIME RATES**

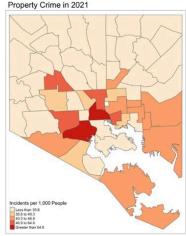
Property Crime in 2017



Property Crime in 2020



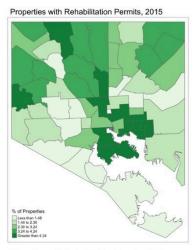




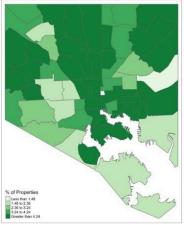
Source: Author's calculations using Baltimore Police Department data, 2015-2021.

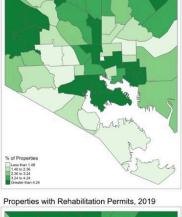
## **APPENDIX F.4: PROPERTIES WITH REHABILITATION PERMITS**

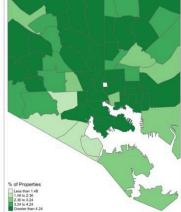
Properties with Rehabilitation Permits, 2016



Properties with Rehabilitation Permits, 2018





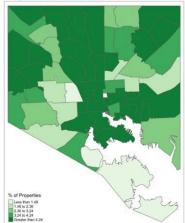


Properties with Rehabilitation Permits, 2021

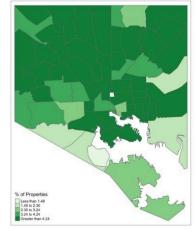




Properties with Rehabilitation Permits, 2017



Properties with Rehabilitation Permits, 2020

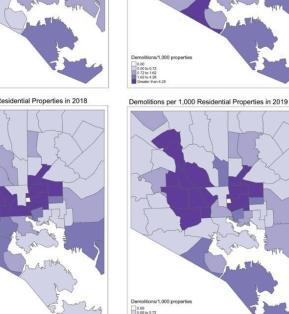


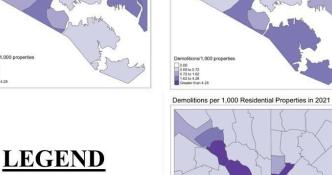
Source: Author's calculations using Baltimore Department of Housing and Community Development data, 2015-2021.

## **APPENDIX F.5: DEMOLITIONS PER 1,000 RESIDENTIAL PROPERTIES**

Demolitions per 1,000 Residential Properties in 2016

Demolitions per 1,000 Residential Properties in 2015

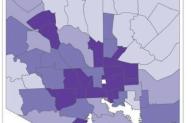




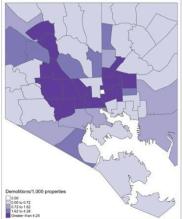
Demolitions/1,000 properties

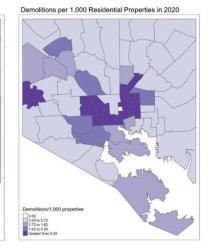


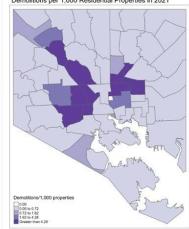
00 to 0.72 72 to 1.62 62 to 4.28



Demolitions per 1,000 Residential Properties in 2017

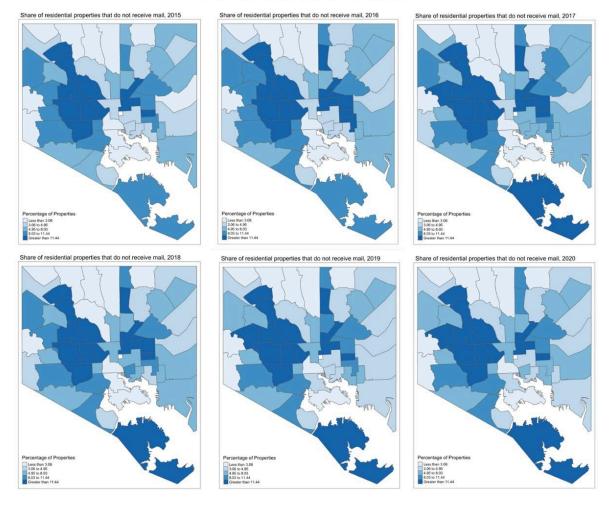


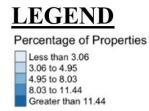




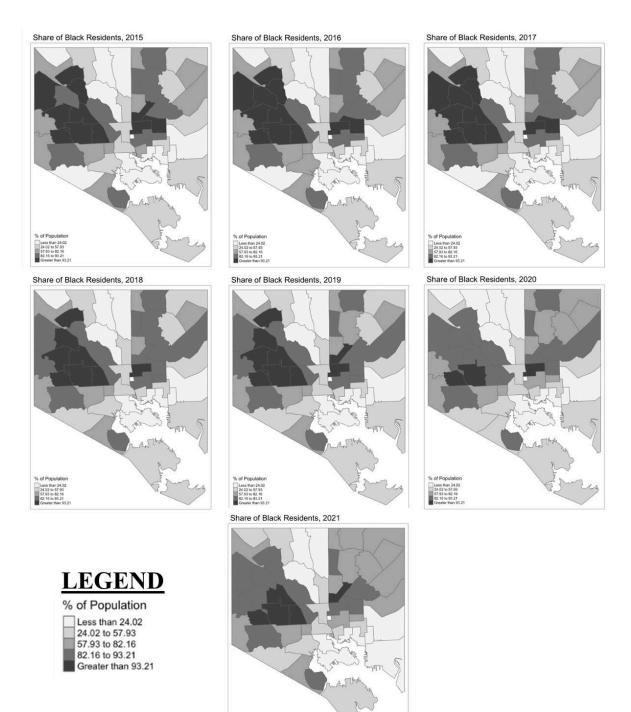
Source: Author's calculations using Baltimore Department of Housing and Community Development data, 2015-2021.

## APPENDIX F.6: SHARE OF RESIDENTIAL PROPERTIES THAT DO NOT RECEIVE MAIL

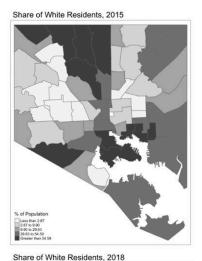




Source: Author's calculations using Baltimore Department of Housing and Community Development data, 2015-2020.



#### **APPENDIX F.7: SHARE OF BLACK RESIDENTS**

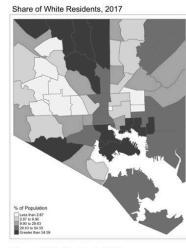


### **APPENDIX F.8: SHARE OF WHITE RESIDENTS**

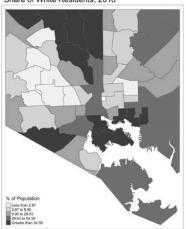
Share of White Residents, 2016

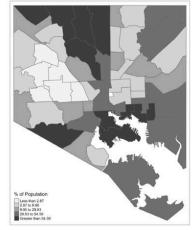
A of Population The Mark 28 of 20 o

Share of White Residents, 2019



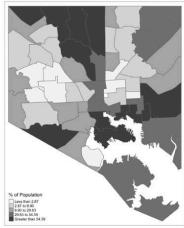
Share of White Residents, 2020





Share of White Residents, 2021

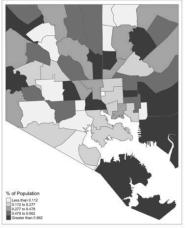




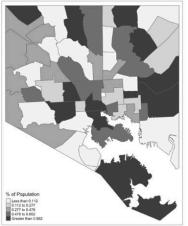
### **APPENDIX F.9: POPULATION SHARE OF ALL OTHER RACES**

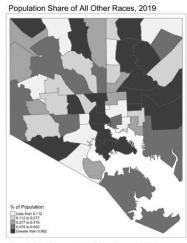
Population Share of All Other Races, 2016

Population Share of All Other Races, 2015



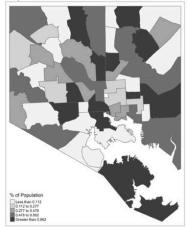
Population Share of All Other Races, 2018





Population Share of All Other Races, 2021

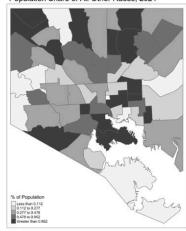
Population Share of All Other Races, 2017



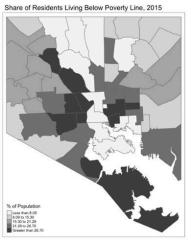
Population Share of All Other Races, 2020



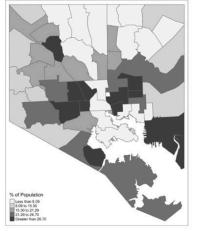




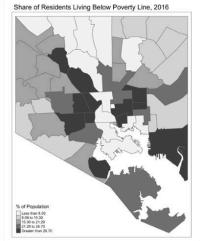
## APPENDIX F.10: SHARE OF RESIDENTS LIVING BELOW THE POVERTY LINE



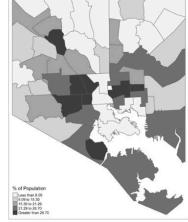
Share of Residents Living Below Poverty Line, 2018



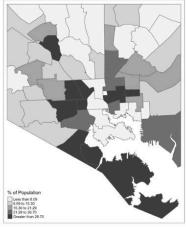




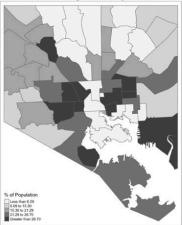
Share of Residents Living Below Poverty Line, 2019



Share of Residents Living Below Poverty Line, 2021



Share of Residents Living Below Poverty Line, 2017



Share of Residents Living Below Poverty Line, 2020

