ABSTRACT

Title of Thesis:	RACE, DISADVANTAGE, AND THE PROBABILITY OF ARREST: A MULTI-LEVEL STUDY OF BALTIMORE NEIGHBORHOODS (2016-2018)
	Madisen Taylor Placzkowski, Master of Arts, 2024
Thesis Directed By:	Associate Professor, María B. Vélez, Department of Criminology and Criminal Justice

This study examines the relationship among neighborhood racial composition, concentrated disadvantage, and the probability of an arrest following a Part 1 crime report. Racial threat theory predicts that as the proportion of Black residents increases over time (dynamic proxy for racial threat), the use of formal social control will increase, while the benign neglect hypothesis predicts that formal social control will diminish in areas with relatively higher proportions of Black residents (static proxy for racial threat). I test racial threat theory and the benign neglect hypothesis for both citizen-initiated and officer-initiated Part 1 crime reports, using Baltimore Police Department crime reports and arrest data, as well as block group characteristics from the 2011-2015 American Community Survey. Through multi-level modeling and including both static and dynamic measures of racial threat, I find that proportion Black is negatively associated with the probability of arrest; concentrated disadvantage has no effect. This finding supports the benign neglect hypothesis and is robust to alternative model specifications, including controlling for victim gender and race. Implications for policy and theories in the conflict tradition are discussed.

RACE, DISADVANTAGE, AND THE PROBABILITY OF ARREST: A MULTI-LEVEL STUDY OF BALTIMORE NEIGHBORHOODS (2016-2018)

by

Madisen Taylor Placzkowski

Thesis submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Master of Arts
2024

Advisory Committee:
Associate Professor María B. Vélez, Chair
Professor Brian Johnson
Assistant Professor Greg Midgette

Acknowledgements

I am grateful for the support of my peers in the Department of Criminology and Criminal Justice, with additional thanks to my cohort, who have provided me with unconditional support and friendship while writing this thesis. I would like to acknowledge my parents for their steadfast support and encouragement. I am endlessly grateful to my committee members, Dr. Brian Johnson and Dr. Greg Midgette have provided invaluable feedback and support. Finally, words cannot express the deep gratitude for the guidance, mentorship, and support of my chair, Dr. María Vélez. “Thank you” does not seem like enough.

Table of Contents

Acknowledgements ii
Table of Contents iii
List of Tables v
List of Figures vi
Chapter 1: Introduction 1
Importance of Neighborhoods in Criminology 1
Chapter 2: Conceptual Arguments 7
Racial Threat Theory and Related Empirical Evidence 7
Conflict Theories 7
Blalock's Racial Threat Theory 7
Relevant Literature 19
Benign Neglect Hypothesis 21
Baltimore as a Study Setting 26
Baltimore Context as a Majority Black City 26
Baltimore's Residential Segregation and Economic Impact 27
Baltimore's History of Controversial Policing 28
Department of Justice Investigation into BPD 29
Chapter 3: Data 30
Sample 30
Unit of Analysis 30
Analytic Sample Restriction 31
Data Sources 32
Dependent Variable 32
Limitations in Data and Missingness 33
Independent Variables 34
Racial Composition 34
Changes in Racial Composition 34
Concentrated Disadvantage 36
Victim Race and Gender 37
Control Variables 37
Crime Type 37
Police District 38
Seasonality 38
Other Neighborhood Demographics 39
Chapter 4: Analytic Strategy 40
Regression Models 41
Chapter 5: Results 43
Descriptive Statistics 43
Panel A: Call-Level Characteristics 43
Panel B: Block Group-Level Characteristics 45
Baseline Model 46
Racial Composition Change 49
Level Change 49

Categorical Change 50
Race and Gender of Victim 51
Baseline Model 51
Level Change 52
Non-Linear Measures of Racial Composition 53
Chapter 6: Discussion and Conclusion 55
Current Study 55
Alternative Explanations 59
Implications 61
Limitations and Future Research 62
Conclusion 64
Appendices 66
Tables and Figures 66
Appendix A. Summary of Racial Threat Tests with Arrest as the Outcome 88
Appendix B. Additional Descriptive Tables 94
Appendix C. Nonlinear Forms of the Relationship between Racial Composition and Probability of Arrest 104
Bibliography 108

List of Tables

Table 1. Block groups with Negative, No, and Positive Percent Change in Proportion Black and Proportion White 66

Table 2. Descriptive Characteristics for Level 1 Variables and Level 2 Variables 67

Table 3. Building the Baseline Model 68

Table 4. Baseline Regression of Crime and Neighborhood Characteristics on Probability of Arrest 72

Table 5. Regression of Crime and Neighborhood Characteristics on Probability of Arrest with Dynamic Measures of Threat 73

Table 6. Regression of Crime and Neighborhood Characteristics on Probability of Arrest with Victim Characteristics and Dynamic Measures of Threat 78

Appendix B. Additional Descriptive Tables 94

Table 1. City-wide Crime Reports by Part 1 Crime Types 94

Table 2. Block Group Counts of Part 1 Crime Reports by Crime Type 95

Table 3. Block Group Proportion of Crime Types of Part 1 Crime Reports 96

Table 4. City-wide Arrests by Part 1 Crime Type 97

Table 5. Block Group Arrest by Part 1 Crime Type 98

Table 6. Block Group Percentage of Calls that Resulted in Arrest by Part 1 Crime Type 99

Table 7. City-Wide Call-Level Variables 100

Table 8. Block-Group Call-Level Variable Counts 100

Table 9. Block-Group Call-Level Variable Percentages 101

Table 10. Block-Group Neighborhood Characteristics 102

Appendix C. Nonlinear Forms of the Relationship between Racial Composition and Probability of Arrest 104

Table 1. Regression of Crime and Neighborhood Characteristics on Probability of Arrest with Nonlinear Measures of Racial Composition 104

List of Figures

Figure 1. Predictive Probability of Arrest by Block Group Proportion Black with 95% CIs.. 81

Figure 2. Predictive Probability of Arrest by Block Group Proportion Black with 95% CIs, Officer-Initiated vs. Citizen-Initiated 82

Figure 3. Predictive Probability of Arrest by Block Group Proportion Black with 95% CIs, Officer-Initiated vs. Citizen-Initiated (Varying slopes) 83

Figure 4. Predictive Probability of Arrest by Block Group Proportion Black with 95% CIs, by Victim Gender 84

Figure 5. Predictive Probability of Arrest by Block Group Proportion Black with 95% CIs, by Victim Race 85

Figure 6. Predictive Probability of Arrest by Block Group Quartile Proportion Black with 95% CIs.. 86

Figure 7. Predictive Probability of Arrest by Block Group Decile Proportion Black with 95% CIs.. 87

Chapter 1: Introduction

Importance of Neighborhoods in Criminology

Neighborhood conditions shape a variety of individual and community-level outcomes, including mental and physical health, education, and socio-economic status (Brooks-Gunn et al., 1993; Chyn & Katz, 2021; Ludwig et al., 2013; Sampson et al., 2002; Wilson, 2012). As such, the neighborhood as a context has been used in formal social control research (e.g., Eitle et al., 2002; Feldmeyer & Ulmer, 2011; Kane et al., 2013; Liska & Chamlin, 1984). Individual-level causal processes may create differences across neighborhoods, or emergent properties of a neighborhood as a whole may cause the aggregate differences (Osgood & Anderson, 2004). Because neighborhoods are more than the sum of their parts, I use multi-level modeling to account for individual-level call characteristics to identify the effect of the emergent properties of neighborhoods.

Police officers can exert formal social control in the form of making an arrest in the process of responding to 911 calls for service or through generating crime reports. Given officers must often respond to calls for service with limited information about the suspect, victim or situation, neighborhood characteristics, including racial composition and concentrated disadvantage, may be helpful in providing police officers with additional context to fill in those gaps (Braga et al., 2019; Smith, 1986). Moreover, the neighborhood context can signal extralegal factors such as suspect and victim's race and socioeconomic status that police officers use to evaluate and act in specific situations (Hasenfeld, 2000; Kahn & Davies, 2017;

Mennerick, 1974; Raaphorst & Van de Walle, 2018; Terrill & Reisig, 2003; Werthman & Piliavin, 1967).

To understand the role of racial composition and concentrated disadvantage in the use of formal social control by police, I consider two theories from the conflict tradition: racial threat theory (RTT; Blalock, 1967) and the benign neglect hypothesis (BNH; Liska & Chamlin, 1984) which offer differing predictions on perceived racial threat and subsequent formal social control. Although race and socioeconomic status are often collinear, here I consider their relationships with formal social control independently. Thus, "minority group" is used to describe either a racial minority group *or* a marginalized socioeconomic group. Racial threat theory predicts that as the percentage of the minority population increases in an area, so will the exertion of formal social control (i.e., dynamic model of threat) [1]. With arrests as a mechanism of formal social control, RTT predicts arrests to increase in areas with increasing minority populations.[2] On the other hand, BNH employs a static measure of racial threat, and anticipates that areas with higher proportions of minority residents will receive less attention and justice from police (lower probability of arrest) because those areas are socially and physically distant from predominately majority neighborhoods (Liska & Chamlin, 1984). Both RTT and the BNH are described in

---

[1]Initially, only the Black population was included but RTT has since been extended to include other racial and ethnic minority groups (Smith, 2021).

[2] For clarity, I use the term "majority group" or "majority" as it is generally conceptualized within the United States as those with political or economic power, generally referring to White people (Marier & Fridell, 2023) and conversely "minority group" to refer to racial or ethnic groups that are non-White (e.g., Black, Hispanic). Additionally, I use the terms "numerical majority" or "numerical minority" to refer to the population proportion of the racial or ethnic group.

more detail in Chapter 2. In this study, I employ a dynamic measure of threat that is consistent with RTT (change in proportion of the Black population by block-group), as well as a stable measure of threat (current proportion of the Black population by block-group) consistent with BNH.

I also extend the literature by distinguishing between citizen-initiated calls for service and officer-initiated interactions. The majority of police officers' day-to-day activities are responding to citizen-initiated calls for service (Varano et al., 2009), yet much of the extant literature on the relationship between neighborhood context and the probability of arrest has not distinguished between citizen-initiated and officer-initiated contacts. Citizen-initiated contacts differ from officer-initiated contacts in several important ways. First, citizen-initiated contacts are situations in which citizens believe police intervention is wanted or necessary, which is not always the case with officer-initiated contacts, especially in minority neighborhoods (Boehme et al., 2022). Second, officers are fulfilling the "helping" aspect of their job when responding to citizen calls rather than exercising their authority (Bercal, 1970). The probability of utilizing arrest while fulfilling their "helping" role may be different than the probability of arrest when officers are exercising their authority while surveilling their patrol area. In other words, officers may differentially utilize their power to arrest depending on the role they are operating within, as well as how that role interacts with the neighborhood context. For example, officers may be seeking justice for the victim during citizen-initiated interactions and exerting formal social control on suspects during officer-initiated interactions. Perhaps officers view victims in predominately minority neighborhoods as less deserving of justice (Klinger, 1997), while they may view suspects in those neighborhoods as more deserving of formal social control. In summary, this study will expand on the body of literature exploring how neighborhood characteristics are related to the probability of arrest, specifically distinguishing between citizen-initiated interactions and officer-initiated interactions.

In this paper, I specifically examine the relationship between neighborhood racial composition and concentrated disadvantage and the probability of arrest following calls for service in Baltimore from 2016 to 2018 (Crimes Known to Police Data: 2016-2018 and Calls for Service Data: 2016-2018). Because conflict theories have been predominately tested in locations where the majority of the residents belong to the dominant group, Baltimore, as a majority-minority city, provides a unique setting to test RTT and BNH. Given the increasing proportion of the minority population in the United States, it is important to understand how existing conflict theories and power structures, such as the criminal justice system, operate in places that already have a majority-minority population. Understanding how racialized power structures operate under these changing racial demographics can inform both theory development and policy as racial demographics continue to shift in the US. I use multi-level modeling to explore if, and how, the probability of arrest differs by neighborhood racial composition and concentrated disadvantage, controlling for call characteristics (i.e., type of crime, use of a gun) and victim characteristics (i.e., victim race and gender). Additionally, I distinguish between citizen-initiated and officer-initiated crime reports, use dynamic and static measures of racial threat (i.e., change in racial composition over time and fixed racial composition), and examine multi-level nested effects (i.e., calls nested within neighborhoods).

In summary, this study contributes to the existing literature in three ways. First, the current study is one of the first multi-level studies that investigates the relationship between neighborhood characteristics and probability of arrest as a form of formal social control by employing both dynamic and static measures of threat. The second contribution of the present study is to investigate potential differences in the effect of neighborhood characteristics between citizen-initiated calls for police service and officer-initiated encounters. The third contribution of this study is testing RTT and BNH in a majority-minority city, a context that has been understudied in the conflict tradition.

The Impact of Formal Social Control

Immediate Impact

The use of arrest as a form of formal social control is important to study because it has real-world consequences. An arrest can have negative consequences on the person arrested as well as on their family, including negative employment outcomes and increased future contact with the criminal justice system (Beardslee et al., 2019; Uggen et al., 2014). Beyond these individual effects, high arrest rates can have negative effects on the community including impaired labor and marriage markets (Clear, 2008). On the other hand, low arrest rates relative to the crime rate (i.e., clearance rates) can also have a negative effect on a community as it may allow criminal activity to flourish, increasing risk of victimization for community residents (Lewis & Usmani, 2022). Perceptions of both underpolicing and overpolicing are associated with perceptions of structural racism in policing, as well as lower perceptions of procedural justice (Jackson et al., 2023). When community members do not feel that police act in a procedurally just manner, there are long-term consequences for the police-community relationship (Sunshine & Tyler, 2003).

Long-term police-community relations

Beyond the individual- and community- level consequences of arrest rates that are either disproportionately high or disproportionately low, the inappropriate use of policing as a mechanism for social control can have long-term consequences for police-community relations. Perceptions of both over-policing and under-policing can reduce citizen trust in police, which makes subsequent formal social control less effective (Boehme et al., 2022). Given that the harms of both over-policing and under-policing are concentrated in neighborhoods with higher proportions of minority residents, these problems can exacerbate already-strained police-community relationships, particularly in minority neighborhoods (Weitzer et al., 2008).

Chapter 2: Conceptual Arguments

Racial Threat Theory and Related Empirical Evidence

Conflict Theories

One way to understand police actions is through the lens of conflict theories. Conflict theories argue a society consists of a dominant group (e.g., racial majority) and marginalized groups (e.g., racial minorities), and law enforcement is one tool the dominant group uses to maintain their power (Snipes et al., 2019). By exerting formal social control, the dominant group is able to limit the amount of social, political, and economic power that others gain which might threaten their interests (Blalock, 1967). Blalock's (1967) RTT predicts that as minority populations increase, the majority feels increasingly threatened and consequently, leverages increased social control. Conversely, BNH contends that formal social control occurs more strongly in places where the majority of residents are of the dominant group, and places that are largely occupied by people of the minority group are neglected (Liska & Chamlin, 1984).

Blalock's Racial Threat Theory

In addition to advancing a theoretical framework for understanding macro-level patterns of interactions between minority and majority groups, including many aspects of discrimination and prejudice, status consciousness, and status prejudice, Blalock (1967) proposed RTT. Racial threat theory posits that as those in power (i.e., the majority or dominant group) feel increasingly threatened by minority groups, they will seek to exert more formal social control to maintain their dominant position in society and control the minority groups that are posing these perceived threats.

Specifically, RTT predicts that as the proportion of the minority population of residents grows, the dominant group will perceive greater levels of threat and exert more formal social control.

The criminal justice system is one tool used by the dominant group, those in power, to “maintain their positions of dominance and control minority populations that pose potential threats” (Feldmeyer & Cochran, 2018, pg. 283). Within the empirical literature, formal social control has been operationalized using either capacity for crime control (e.g., police force size; Stultz & Baumer, 2007) or actual crime control (e.g., arrest rates; Eitle & Monahan, 2009). At the neighborhood level, RTT predicts that police will exhibit more crime control (i.e., arrest rates) in neighborhoods with an increasing proportion of racial minority residents (e.g., Black residents).

Racial threat theory has been empirically tested within the extant literature, with varying methods and results. While some of this literature has examined RTT on the potential for social control (e.g., police force size) or in the context of courts and sentencing, perceptions of threat, and laws and policies, here, I will focus this review on the tests of formal enacted social control through law enforcement (i.e., arrests). Fifteen empirical studies were identified that investigated aspects of these theories in a variety of contexts[3].

[3] Table 1 in the Appendix A provides an overview of the 15 extant studies published between 1984 and 2021, that test RTT through formal social control in the form of arrests, along the following dimensions: context, citizen- or officer- initiated calls, threat measure(s) (and whether they used static or dynamic measure(s)), unit(s) of analysis, whether it is a single-level or multi-level statistical test(s), outcome measure(s), and the main findings.

Sources of racial threat. Within RTT, Blalock (1967) proposed two main sources of racial threat: economic competition and political power. As the minority group population grows, they are more likely to be able to compete economically and vie for political power (Feldmeyer & Cochran, 2018). Economic threat has been measured in terms of disadvantage or racial/ethnic inequality in unemployment (Andersen, 2015; Eitle &Monahan, 2009; Huff, 2021; Kirk & Matsuda, 2011; Kirk, 2008; Liska & Chamlin, 1984; Lum, 2011; Ousey & Lee, 2008; Stolzenberg et al., 2004; Stucky, 2012), political threat measured as the presence of a Black mayor (Eitle & Monahan, 2009) or the ratio of Black-to-White voter turn-out (Eitle et al., 2002), and crime threat measured by level of Black-on-White crime (Eitle et al., 2002).

Although Blalock only mentioned competition and power as sources of threat, others have included fear of criminal victimization via Black-on-White crime as a source of perceived threat. Several criminologists have argued that an increase in Black-on-White crime can lead to increased perceptions of racial threat (Chamlin & Liska, 1992; Eitle et al., 2002; Liska & Chamlin, 1984). Yet, even in the absence of actual increases in Black-on-White crime, minority groups are often perceived as criminal threats, and an increase in the percentage of the population that belongs to the minority group could be perceived as increased potential for crime victimization (Liska, 1992; Liska et al., 1981, 1985).

Although political, economic, and criminal threat are theoretically distinct manifestations of threat, racial composition is a crude measure of threat as it cannot distinguish between the types of threat. Of the studies that use racial composition as a proxy for racial threat, most use the proportion of Black residents (e.g., Andersen, 2015; Gaston, 2019; Parker et al., 2005; Stolzenberg et al., 2004; Stucky, 2012); however, some use the proportion of Hispanic residents (Andersen, 2015; Huff, 2021; Levchak, 2017). Eitle and Monahan (2009) used a binary variable to differentiate between cities with populations that were greater than or less than 40% Black.

Yet, others have considered the proportion of minority residents as an imperfect proxy for the actual concept of threat perceived by the dominant group (Feldmeyer & Cochran, 2018). Subsequent empirical research has used racial segregation and concentrated disadvantage as potentially better measures of racial threat (Eitle & Monahan, 2009; Kirk & Matsuda, 2011; Kirk, 2008; Liska & Chamlin, 1984; Ousey & Lee, 2008; Stolzenberg et al., 2004). Racial residential isolation and concentrated Black economic disadvantage amplify awareness of group differences, increasing racial conflict and anti-Black dispositions among White people (Liska, 1992; Liska et al., 1981; Parker et al., 2005). This increased perceived threat due to segregation and concentrated disadvantage is argued to lead to increased levels of formal social control (Parker et al., 2005).

Functional form. Blalock (1967) proposed a more detailed and nuanced description of the relationship between the relative size of the minority group and discrimination. Racial threat theory specifically looks at formal social control as an expression of discrimination, but Blalock proposed this relationship for all forms of discrimination. According to Blalock, discrimination should be low when the minority group is a small proportion of the total population and increase as the minority population proportion grows. He predicts discrimination will grow in a curvilinear fashion, with the specific shape of that curve varying by the type of threat perceived. He described the discrimination growth curve for two types of threat, (a) economic competition and (b) power threat. In situations of economic competition, Blalock describes the discrimination growth curve as an “inverted U-Shape,” with the slope of discrimination increasing at a decreasing rate (Blalock, 1967; pg. 149). However, his illustration of that plateaus near the apex (not descending as implied by the descriptor “U-Shaped”). Blalock did not specifically offer a prediction about the relationship between criminal threat and discrimination, as the criminal threat element was incorporated into the theory later by Liska and colleagues (1985), who argue non-White groups can also be perceived as a criminal threat to White dominance. Since the hypothesized functional form depends on the type of threat, and the current study does not distinguish specific types of threat, the functional form in this context is not clearly predicted. Therefore, the current study focuses on the linear relationship (positive or negative) between the neighborhood characteristics and probability of arrest, with a preliminary exploration into nonlinear relationships.

Change over time. Blalock specifically traced increases in the proportion of the minority population to racial threat. In other words, those in the majority group will feel more threat in places with increasing proportions of minority residents than in places with stable proportions of minority residents (i.e., a dynamic measurement of racial composition). However, most racial threat studies have simply used a static measure of threat (e.g., proportion of minority population). Conversely, BNH predicts that areas with large populations of minority residents will be neglected, regardless of change over time, and formal social control will be decreased in areas with large populations of residents in the dominant group (Parker et al., 2005).

Thirteen studies used a static measure of threat, which measures the proportion of the minority population at one point in time (Andersen, 2015; Eitle & Monahan, 2009; Eitle et al., 2002; Gaston, 2019; Huff, 2021; Kirk & Matsuda, 2011; Kirk, 2008; Levchak, 2017; Liska & Chamlin, 1984; Lum, 2011; Ousey & Lee, 2008; Stolzenberg et al., 2004; Stucky, 2012). The findings of these studies were split between support for RTT and BNH. However, two studies also used a dynamic measure of threat, such as change in racial composition over time (Kane et al., 2013; Parker et al., 2005), which is more in line with Blalock's (1967) theory on racial threat perceptions increasing as the proportion Black increases over time in one place. Kane and colleagues (2013) found support for RTT, while Parker and colleagues (2005) found support for BNH. Thus, the difference between using a static measure and using a dynamic measure does not seem to be related to the contradictory findings.

Formal social control. In response to increased feelings of threat, the dominant group is likely to increase social control as a means of controlling the minority groups who pose potential threats and maintain their position of dominance (Feldmeyer & Cochran, 2018). Blalock (1967) does not elaborate on the specific methods or forms of control that might be used and provides little about the criminal justice system as a mechanism for formal social control. Explicit links between racial threat and the criminal justice system were introduced by Turk (1969) and Blauner (1972) who proposed that both law formation and law enforcement are two primary tools used to control a minority group. Arrests and criminal convictions reduce minority populations' capacity to compete economically and politically, as well as controlling perceived criminal threats.

Many of the extant studies focus on the use of formal social control in the form of arrests, and the specific outcomes are either arrest rates (Chamlin & Liska, 1992; Eitle & Monahan, 2009; Kirk, 2008; Liska & Chamlin, 1984; Ousey & Lee, 2008; Parker et al., 2005; Stucky, 2012), or probability of arrest (Andersen, 2015; Gaston, 2019; Huff, 2021; Kirk & Matsuda, 2011; Levchak, 2017; Lum, 2011; Stolzenberg et al., 2004). Some studies included all arrests, whereas others focused on arrests for a specific crime type, such as drug arrests (Eitle & Monahan, 2009; Gaston, 2019) or violent arrests (Eitle et al., 2002; Stolzenberg et al., 2004; Stucky, 2012). Some of these studies examined total arrest rates (Chamlin & Liska, 1992; Gaston, 2019; Huff, 2021; Kirk & Matsuda, 2011; Kirk, 2008; Liska & Chamlin, 1984; Lum, 2011), while others disaggregated and looked at race-specific arrests separately (Eitle & Monahan, 2009; Stolzenberg et al., 2004; Stucky, 2012), or examined the disparity between Black and White arrests (Eitle et al., 2002; Ousey & Lee, 2008; Parker et al., 2005). Andersen (2015) included only youth arrests. The current study investigates the arrest probabilities for all Part 1 crimes (homicide, rape, robbery, aggravated assault, burglary, larceny, and motor vehicle theft).

Citizen-initiated calls and conflict theory. Conflict theory is relevant when examining social control in the form of officer-initiated interactions, such as vehicle stops or searches and frisks. However, officers are also able to exert social control in response to citizen-initiated interactions (e.g., 911 calls for service) because officers continue to be in a position of authority and power in the interaction, since they are empowered by the state to detain, arrest, and use force, regardless of who initiated the interaction. Thus, the power dynamic favors officers, even when the citizen initiated the interaction, which makes conflict theory relevant.

Most of the reviewed studies did not distinguish between arrests that were made because of officer-initiated or citizen-initiated interactions and included arrests for crimes that come to the attention of police through a variety of means. However, Levchak (2017) examined only arrests that were the result of an officer-initiated stop or interaction. Huff (2021) is the only study that controlled for whether the contact was citizen- or officer- initiated and found that arrests were more likely in officer-initiated contacts, although these contacts only made up about 14% of all police-citizen interactions. The current study distinguishes between citizen-initiated and officer-initiated contacts ending in arrests, since these may represent fundamentally different expressions of state power. Specifically, it is useful to parse out how RTT or BNH are either supported or not supported within citizen-initiated and officer-initiated calls, since citizen-initiated and officer-initiated interactions represent different kinds of interactions within the power structure.

General findings of racial threat theory tests. In summary, the findings of the reviewed studies on the relationship between racial composition and arrests are mixed. Some prior studies found unconditional support for RTT, in that proportion Black was positively related to arrest rates or probability of arrest (Gaston, 2019; Huff, 2021; Liska & Chamlin, 1984). Others found conditional support for RTT, where only some types of threat were associated with higher arrest rates but not others (Eitle & Monahan, 2009; Eitle et al., 2002). Kane and colleagues (2013) specifically found that change in proportion Black was associated with higher arrests, but only in majority White neighborhoods. Some studies found no relationship between racial composition and arrest rates or probabilities after controlling for other relevant factors (Kirk, 2008; Levchak, 2017; Ousey & Lee, 2008). Finally, some studies found support against RTT and in support of BNH, or that the proportion Black is negatively associated with arrest rates or probabilities (Andersen, 2015; Kirk & Matsuda, 2011; Lum, 2011; Parker et al., 2005; Stolzenberg et al., 2004; Stucky, 2012). Of the reviewed studies, support for BNH was slightly more likely than support for RTT. However, this varied across specific dimensions of the studies. For example, studies were more likely to find support for RTT in contexts that were racially split rather than majority White, when studies only included racial composition as a measure of threat, and in units of aggregation smaller than a city. Even so, differences in these elements of the studies do not totally explain the difference in findings. Thus, the extant literature has not clearly adjudicated the relationship between racial composition and the probability of arrest. Within this current study, I aim to add to this conversation by examining racial threat in a majority Black city, differentiating between crime reports that result from citizen-initiated versus officer-initiated contacts, and using a multi-level model with a dynamic measure of threat.

Majority-minority places and conflict theory. The population in the United States is becoming increasingly non-White (US Census, 2020). For the first time in our history, the White population declined in proportion between the 2010 and 2020 census, and non-White racial and ethnic groups are growing in both absolute numbers and proportion (Frey, 2020). Growing numbers of people in racial and ethnic minority groups accounted for all the population growth in the United States in the last decade (Frey, 2020). In 1980, White people comprised almost 80% of US residents, and in 2020, account for about 60% (US Census, 2020). This demographic change is driven by several factors, including an older White age structure and lower White birth rate, as well as increasing immigration (Frey, 2020). As the racial and ethnic makeup of the United States continues to change, it is increasingly important to study conflict theories in places that already have a majority-minority population. Although conflict theory, and specifically RTT, examines the impact of increasing minority populations, it assumes a White majority (at least in the US context). However, there is little theoretical development or empirical testing of conflict theories in contexts where White people are not the numerical majority (Vélez & Peguero, 2023).

Racial threat theory predicts that as the proportion of minority residents increases in a neighborhood, so does formal social control (i.e., the probability of arrest). Locations with ample opportunities for majority and minority population interaction (and thus, opportunities to allow the dominant population to perceive a threat) are also ideal locations for empirically investigating RTT. However, most studies have examined this relationship in contexts where the racial majority (White people) is also the numerical majority. Most of the reviewed studies examine cities nation-wide, and therefore reflect the general context of the United States, which is currently majority White (Andersen, 2015; Eitle & Monahan, 2009; Levchak, 2017; Liska & Chamlin, 1984; Ousey & Lee, 2008; Parker et al., 2005; Stolzenberg et al., 2004; Stucky, 2012). Of the studies that examined a specific city, most were cities with a majority White population (Eitle et al., 2002; Kirk &Matsuda, 2011; Kirk, 2008; Lum, 2011) or cities with an even split between White and Black populations (Gaston, 2019) or White and Hispanic populations (Huff, 2021). Only one of the reviewed studies took place with a majority Black population, and they found support for RTT (Kane et al., 2013).

Minority residents may experience the same formal social controls exerted by the politically and economically dominant group, even in cities in which they are the numerical majority of the population. The tenants of conflict theories may still apply. As such, I aim to evaluate RTT, by investigating the relationship between racial composition and concentrated disadvantage, and the probability of arrest within Baltimore, a location that has a city-wide majority Black population, as well as large numbers of neighborhoods that vary in their levels of racial segregation.

Conflict theories, including RTT and BNH, also apply to contexts where the racial "minority" (in this case, Black people) is the numeric majority, as is the case in Baltimore. While Black Baltimore residents do have substantial political power, with a majority of city council members being Black and having a Black mayor, the ongoing racial unrest indicates that Black residents continue to feel marginalized (Mozingo & Phelps, 2015). Further, Black residents are not the economically dominant group. Black residents account for more than three-fourths of all Baltimore residents living in poverty (approximately 100,000 people) and are of the least upwardly mobile in the country (Investigation of the Baltimore City Police Department, 2016). This highlights that a Black political majority is not necessarily enough to make Black people feel that they are the dominant group in an area (Blake, 2015).

Beyond this, police-community tensions are typically centered along racial lines. In a city where the majority of residents are Black, Baltimore police officers are primarily White and male, and do not live within the city of Baltimore[4]. Therefore, police officers, and the department as a whole, may have interests that do not align with those of city residents, which provides a context ripe for conflict. The Department of Justice (DOJ) investigated BPD starting in 2016 and highlighted the place-based nature of the tensions between police and the community, and how this relationship differs across neighborhoods. They note that BPD has targeted certain Baltimore neighborhoods in a way that disproportionately harms Black residents. Unconstitutional stops were concentrated in predominantly Black neighborhoods, and these stops frequently lack reasonable suspicion. Residents in wealthier and largely White neighborhoods reported that officers were respectful and responsive to their needs, while residents from mostly Black neighborhoods felt that officers were often disrespectful and did not respond quickly to their calls for service (Investigation of the Baltimore City Police Department, 2016).

Finally, tremendous residential segregation characterizes Baltimore. Although Baltimore as a whole is a majority-Black city, where the average block group is 66.8% Black, there are numerous majority-White neighborhoods where RTT and BNH would be expected to apply as in any other majority-White context. As of 2015,

[4] As of December 31, 2021, there were 2,327 sworn police officers in the BPD, of which 951 (40.8%) were Black, 373 (16%) were female, and 570 (24.5%) were residents of Baltimore City (Baltimore Police Department, n.d.)

there were neighborhoods (16 block groups) where less than 2% of the residents are Black, while other neighborhoods (73 block groups) were entirely Black. Similarly, there were 117 neighborhoods with no White residents, and seven neighborhoods that had up to a 95% White population. There were two majority Hispanic/Latino block groups. Further, Baltimore is residentially segregated by socioeconomic status, such that the percentage of block group residents who are living below the poverty level ranges from 0.00% to 86.70% (m=24.6%, sd=17.2). Parker and colleagues (2005) argued that increased social distance, such as that caused by residential segregation, will amplify perceptions of group differences and thus, perceptions of threat. Therefore, racial and socioeconomic segregation make conflict theories relevant, even in majority-minority contexts.

Relevant Literature

Of the reviewed studies, many have similarities to the current study. Of the studies that examine the relationship between racial composition and arrest rates, several take place in a single city (Gaston, 2019; Huff, 2021; Kirk and Matsuda, 2011; Kirk, 2008; Lum, 2011), including a majority-Black city (Kane et al., 2013). Others have utilized either multi-level modeling (Andersen, 2015; Gaston, 2019; Huff, 2021; Kirk and Matsuda, 2011; Kirk, 2008; Levchak, 2017; Stolzenberg et al., 2004) or dynamic measures of racial composition (Kane et al., 2013; Parker et al., 2005). However, none of these studies have utilized both multi-level modeling *and* dynamic measures of racial composition, leaving a significant gap in the literature. The current study aims to fill this gap. Parker and colleagues (2005) used arrest data for all US cities with more than 100,000 residents. Using both static and dynamic measures of racial composition (% Black and growth in the Black immigrant population), they find support for the benign neglect hypothesis, such that Black arrest rates are lower in cities with a higher proportion of Black residents. Similarly, the current study also utilizes both static and dynamic measures of racial composition. However, Parker and colleagues (2005) did not use multi-level modeling to incorporate characteristics of individual arrests. Therefore, the current study builds on their work by using multi-level modeling and by focusing on a single city that is majority Black.

Kirk (2008) used official arrest data in combination with the PHDCN for sampled individuals in Chicago. He used only a static measure of racial/ethnic composition (% Black and % Latino), but he did incorporate multi-level modeling where individuals are nested within neighborhood clusters. He found that neighborhood racial composition was not associated with racial disparities in arrest growth curves, so there was no evidence of racial threat found in this study. Although Chicago has a substantial Black population, it is a majority White city. While the current study also focuses on arrest probabilities within a single city, I am testing racial threat theory in a majority Black city. I similarly use multi-level modeling to incorporate crime-level characteristics, but I also include dynamic measures of racial composition.

Kirk and Matsuda (2008) also used official arrest data for sampled individuals in the PHDCN in Chicago. They also use multi-level modeling and static measures of percent Black and percent Latino. They found support for benign neglect (although they frame the findings as legal cynicism) since individuals are less likely to be arrested following the commission of a crime in predominantly Black neighborhoods. As above, I improve upon this study by including dynamic measures of racial composition and testing racial threat theory in a majority Black city.

Huff (2021) used Computer-Aided Dispatch (CAD) data from all police-citizen contacts and arrests in Phoenix. She used static measures of racial composition (% Hispanic and % Black) in a multi-level model where incidents are nested within census tracts in Phoenix. She finds support for racial/ethnic threat, where arrest was more likely in neighborhoods that were more Hispanic or Black, after controlling for situational and officer-level characteristics. Importantly, this is the only reviewed study that controlled for whether an interaction was officer-initiated or citizen-initiated, which I also do in the current study. However, I also incorporate dynamic measures of racial composition.

Benign Neglect Hypothesis

Parker and colleagues (2005) argue that social distance is higher when there is little intergroup contact, and that increased social distance heightens perceptions of threat. However, Spitzer (1975) argues that low levels of intergroup contact and increased social distance may reduce feelings of threat, rather than increase them. Highly segregated cities/contexts provide fewer opportunities for interaction between residents of different racial groups, thus segregating potential threats to spaces away from the majority population and in turn, providing fewer opportunities for the majority to perceive a threat. In contexts that are highly segregated, racial composition is negatively associated with perceived racial threat, decreasing the need for formal social control, which is the premise of BNH. Similarly, Black on White crime is less likely when Black people are residentially distanced from Whites. Therefore, larger proportions of minority residents in highly segregated contexts will not necessarily lead to increased perceptions of racial threat or fear of crime.

The BNH provides a possible community-level explanation for the empirical relationship between racial composition and probability of arrest in a highly segregated majority-minority city like Baltimore. The benign neglect hypothesis predicts that the majority group will exercise increased social control when they perceive increased threat, similarly to RTT. However, BNH differs in its prediction about the relationship between racial composition and perceived threat. In contrast to RTT, BNH (Liska & Chamlin, 1984) posits that as the proportion of residents who are Black increases, the level of perceived threat may decrease. This is because as the proportion of residents who are Black increases, a higher proportion of crime is intra-racial, specifically between Black suspects and victims (Andersen, 2015; Chamlin, 1987; Chamlin & Myer, 2009; Kirk & Matsuda, 2011; Myer & Chamlin, 2011; Ousey & Lee, 2008). Non-White intra-racial crime does not pose the same threat to White dominance as inter-racial crimes. In highly segregated cities, such as Baltimore, crimes are more likely to be intra-racial (*New Racial Segregation Measures for States and Large Metropolitan Areas: Analysis of the 2005-2009 American Community Survey*, n.d.). Thus, in areas with high proportions of Black residents, the victim, as well as the suspect, of a crime is more likely to be Black. Therefore, BNH predicts that there is in fact less need for formal social control of the Black population, especially when a city is highly segregated, because the dominant group does not perceive increased threat or fear of crime. Without perceptions of threat, there is no need for the dominant group to enact additional formal social control.

In highly segregated cities, police may exert less formal social control measures in neighborhoods that are majority Black or have higher levels of disadvantage for the following reasons: 1) willingness, 2) ability, and 3) external pressure (Liska & Chamlin, 1984). First, and consistent with BNH, police may be less willing to enact formal social control in neighborhoods where they view crime victims as “less deserving” of justice (Smith et al., 1984). Specifically, police officers may be less willing or less able to enact formal social control in places that they view as “less deserving” of justice because of their social and physical distance from dominant societal groups. As such, BNH predicts that the probability of a police-citizen interaction, especially a citizen-initiated call for service, ending in arrest will be lower in these locations as compared to locations with a lower proportion of Black residents. Disproportionately lower arrest rates means that crime victims are less likely to receive justice. While the term “benign” connotes “not harmful”, neglectful policing can be as harmful as over-policing (Brunson, 2020). Neglectful policing can leave residents feeling unsafe and unprotected by law enforcement (Brunson, 2020). Particularly in neighborhoods with high crime rates, neglectful policing puts residents at risk of continued risk of criminal victimization. Second, regardless of their willingness to enact formal social control, police in disadvantaged areas may have fewer resources to put towards solving crime and committing arrests (Parker et al., 2005). Additionally, there may be lower levels of citizen cooperation with police investigations in these areas due to ongoing tensions with police (Carter & Carter, 2016). In fact, there may even be external pressure for police to engage in less formal crime control following the wave of protests against police use of force and calls for police reform (Marier & Fridell, 2020; Midgette & LaFree, forthcoming). Third, there may be less external pressure for police to engage in formal crime control when crimes are intra-racial (Liska & Chamlin, 1984). From a conflict perspective, intra-racial crimes pose less threat to White power than crimes where the victims are White. Therefore, police may feel less pressure to control intra-racial crime since it poses less threat to the status quo. As the proportion of minority residents increases, relatively more crimes will be intra-racial and involve both a minority suspect and a minority victim.

In summary, RTT and the BNH offer competing predictions for the direction of the relationship among neighborhood racial composition and concentrated disadvantage and the probability of arrest. I test both BNH and RTT by using multi-level models (MLM) because both theories predict that neighborhood characteristics will influence the use of formal social control, controlling for crime type and victim characteristics. Multi-level models that include situational characteristics (i.e., call characteristics and victim characteristics) can more reasonably compare neighborhoods that have differing characteristics.

I hypothesize that both neighborhood racial composition and concentrated disadvantage will be associated with formal social control, measured by the probability of arrest, after controlling for crime type and victim characteristics. More specifically, and consistent with BNH, I hypothesize that the probability of arrest will be lower in neighborhoods with higher proportions of minority residents, as well as lower in neighborhoods with higher concentrated disadvantage in Baltimore, a highly segregated city. Further, I hypothesize that the relationship between neighborhood characteristics and the probability of arrest will differ between officer-initiated and citizen-initiated calls, and I expect the probability of arrest to be higher for officer-initiated calls.

Hypothesis 1a: If racial threat theory holds, crimes that are reported in block groups with relatively higher proportions of Black residents will have a higher probability of ending in an arrest than crimes that are reported in block groups with relatively lower proportions of Black residents.

Hypothesis 1b: If the benign neglect hypothesis holds, crimes that are reported in block groups with relatively higher proportions of Black residents will have a lower probability of ending in an arrest than crimes that are reported in block groups with relatively lower proportions of Black residents.

Hypothesis 2a: If racial threat theory holds, crimes that are reported in block groups with relatively higher levels of concentrated disadvantage will have a higher probability of ending in an arrest than crimes that are reported in block groups with relatively lower levels of concentrated disadvantage.

Hypothesis 2b: If the benign neglect hypothesis holds, crimes that are reported in block groups with relatively higher levels of concentrated disadvantage will have a lower probability of ending in an arrest than crimes that are reported in block groups with relatively lower levels of concentrated disadvantage.

Hypothesis 3: Officer-initiated crime reports are more likely to end in arrest than citizen-initiated calls for service.

Hypothesis 4a: Crimes involving White victims will have a higher probability of arrest than crimes involving non-White victims.

Hypothesis 4b: Crimes involving female victims will have a higher probability of arrest than crimes involving male victims.

Baltimore as a Study Setting

As mentioned, the city of Baltimore provides a robust setting through which to study the relationship between neighborhood racial composition and disadvantage and formal social control (e.g., the probability of arrest) for several reasons. First, Baltimore is a majority Black city, and has been since the 1970s, which allows us to study conflict theories in a majority-minority setting. Second, Baltimore is highly residentially and economically segregated, which provides a further unique element to the setting for testing conflict theories by neighborhood characteristics (e.g., proportion minority population, disadvantage). Third, Baltimore's history of, and ongoing, police-community strain and police department controversies indicate the city has had challenges with race, racial threat, and policing.

Baltimore Context as a Majority Black City

Black residents in Baltimore officially reached a numeric majority in the 1970 Census[5]. Currently, Baltimore has the fifth largest Black population of any U.S. city, despite only being the 30th largest city in the US (US Census 2023 Population Estimates). In many ways, Baltimore exemplifies the changing racial composition of

[5] Baltimore has a proportion of minority residents that is higher than the national average; 61.2% of its residents are Black, 5.9% are Hispanic/Latino, 2.6% Asian, and 28.4% White, compared to the national average of 13.6% Black, 19.1% are Hispanic/Latino, 6.3% Asian, and 75.5% White, 27.6% non-Hispanic White (US Census 2023 Population Estimates).

the country, which is becoming increasingly diverse and less White. As previously mentioned, conflict theories were developed and have largely been tested in contexts with a majority White population. As such, it is important to test and update theories to reflect these changing demographics. Baltimore as a study setting allows me to begin to fill this gap in the conflict literature.

Although the racial composition of Baltimore has been relatively stable at the city-level for several decades, there is substantial change in the racial composition within neighborhoods. This change over time within neighborhoods allows me to test RTT, which requires change in racial composition over time within a place.

Baltimore's Residential Segregation and Economic Impact

Historically, Baltimore has been, and continues to be, a highly racially segregated city, with only about 20% of the neighborhoods being racially integrated [6], making it a relevant city to examine the relationship between race and arrest rates. Generally, conflict theories rely on intergroup contact and interactions. More specifically, RTT argues that as the proportion of Black residents increases, contact between Black and White people will also increase. However, segregation may limit the amount of interracial contact, even in places with a large proportion of Black residents, such as Baltimore. Benign neglect hypothesis posits that segregation reduces perceptions of threat, and consequently the need for social control. Therefore, a setting with significant segregation, such as Baltimore, is an ideal setting to

[6] This calculation is using the current study data, where an integrated neighborhood is one in which no racial/ethnic group (White, Black, or Hispanic) has at least 70% of the population. For more information on classifying neighborhoods, see Peterson and Krivo, 2010.

adjudicate between these competing ideas on the relationship between segregation and perceived threat, and subsequent formal social control.

Baltimore's History of Controversial Policing

Although Baltimore now has a majority of Black residents, the Baltimore Police Department (BPD) was founded in 1874, when White people constituted the numeric majority population in the city, and when racial discrimination was even more rampant. These historical origins may impact the ongoing culture and practices within the BPD, even as the actual racial composition of the city has changed. Therefore, it is important to consider the history of the BPD, and particularly its relationship with Black residents, when examining the current use of arrest.

Baltimore Police Department's misconduct became the center of a national debate following the death of Freddie Gray, a Black Baltimore resident, in police custody on April 19, 2015. Following his arrest for allegedly carrying a switchblade, Freddie Gray was placed, unsecured into a van, where he became unconscious and suffered spinal cord injuries (US Department of Justice, 2017). Baltimore residents protested the conduct of BPD over the next two weeks, with peaceful protests evolving into property destruction, looting, and violence (Yan & Ford, 2015). Beyond the City of Baltimore, these protests spread across the country and became part of a series of nationwide protests against police brutality and misconduct as part of the Black Lives Matter movement (Hartmann, 2015). All six officers involved in Freddie Gray's arrest were charged with offenses including homicide, but all charges were either dismissed or the officers were acquitted by the summer of 2016 (US Department of Justice, 2017).

Department of Justice Investigation into BPD

In response to Freddie Gray's death and the subsequent protests, the Department of Justice (DOJ) conducted an investigation into the BPD, and determined that BPD had engaged in a pattern of unconstitutional conduct, including unconstitutional stops, searches, and arrests, using enforcement strategies that produce unjustified racial disparities in the rates of stops, searches, and arrests, using excessive force, and retaliating against people engaging in expression protected by the First Amendment (Investigation of the Baltimore City Police Department, 2016). Although Freddie Gray’s death precipitated the DOJ Investigation, the DOJ noted the problems in the BPD had been ongoing and that the conduct that resulted in Freddie Gray’s death was not simply because of “a few bad apples” in the department, but rather systemic deficiencies in the BPD that fail to equip officers with the resources needed to police safely, constitutionally, and effectively, and fails to hold officers accountable for misconduct (Investigation of the Baltimore City Police Department, 2016).

As a result of their investigation, the City of Baltimore and the DOJ entered into a consent decree in April 2017 that required BPD to commit to policing reforms and more transparently share their data. The data that is publicly available as part of this consent decree is used in this current study.

Chapter 3: Data

Sample

Unit of Analysis

This study investigates the role of community-level sources of variation in the risk of arrest following a Part 1 crime report, written following either a citizen-initiated call for service or an officer-initiated contact. As this is a multi-level analysis, I have two units of analysis. Part 1 crime reports (either from citizen-initiated 911 calls for service or from officer-initiated reports) are the level 1 unit of analysis, which are nested within neighborhoods, the level 2 unit of analysis. While "neighborhoods" can be defined in many ways, I utilize census block groups to capture neighborhoods. Block groups are both large enough and have sufficient number of crimes within them in Baltimore to facilitate accurate and statistically powerful multi-level models (Hox, 1998) and yet small enough to pick up on community dynamics. Other studies have used the larger Community Statistical Areas (CSA) which are a larger area than what is typically considered a neighborhood (Weisburd et al., 2020). While census tracts are smaller than CSAs, they are large enough to include heterogeneity and may mask nuanced neighborhood characteristics. A census tract can include substantial spatial variation in both racial composition and concentrated disadvantage *within* each tract, which may attenuate the true effect of these characteristics at the neighborhood level. Further, because police structure their behavior in smaller geographic areas (similar to crime hot spots), a smaller unit of analysis such as block groups may be more appropriate in studies of policing than a larger unit such as census tracts (Weisburd et al., 2020). As such, block groups are a meaningful unit of analysis since they are small enough to represent more homogenous geographic areas.

Both the number of groups and the sample size within each group is important for statistical power in MLM analysis. There is a general rule that MLM analysis should have a sample of at least 30 level 2 groups with at least 30 level 1 units per group (Hox, 1998). This general rule is met with the data used in this study, since there are 643 groups (block groups), and the lowest number of calls per block group is 10. A large number of groups is more important for accuracy and power than a large number of individuals within each group (Hox, 1998). Wooldredge (2002) found that results tend to be consistent across several levels of spatial aggregation, so my findings may not have been impacted by the choice of block groups over census tracts.

Analytic Sample Restriction

In Baltimore City, there are 653 block groups as of the 2010 Census. However, 10 block groups have fewer than fifty residents and are thus excluded from the present analysis, since block groups with fewer than fifty residents are unlikely to represent a meaningful social area. Since RTT is about where people in the minority group *live*, places where very few people of any racial group live are unlikely to be relevant for tests of RTT. The analytic sample is comprised of 112,314 Part 1 crime reports made within 643 block groups that are home to a total of 616,480 residents.

Data Sources

The data used within this study were drawn from several sources including BPD crime and arrest data, decennial Census data, and the American Community Survey (ACS). Data were provided by BPD that includes 911 Calls for Service and the Crimes Known to Police, which were merged with arrest information for all Part 1 Crimes between January 1, 2016, and December 31, 2018. This data set contains incident-level call data from all 911 calls responded to by the BPD. When multiple calls were made about the same incident, only the first call is kept in the dataset. Additionally, this dataset contains information about officer-initiated crime reports. The dependent variable is measured using a binary variable indicating whether an arrest was made following either a citizen-initiated 911 call or officer-initiated report. The dataset provided includes information on the type of Part 1 crimes reported, the block location of the calls (e.g., the 1900 block of Independence Ave.), and if arrests were made in connection with that call. Each call is geocoded into its corresponding block group. I selected a three-year time period (January 1, 2016 to December 31, 2018) for this study because a three-year average is the standard in the literature and can smooth out random yearly fluctuations in crime (Light & Ulmer, 2016). Finally, the ACS data were used to provide five-year estimates (2011-2015) for block group demographic characteristics.

Dependent Variable

The dependent variable of interest in this study is the probability of a 911 call culminating in an arrest. Over the three-year study period, 1,251,716 citizen-initiated calls were made that resulted in 92,649 Part 1 crime reports[7] by the police, and 19,665 officer-reported Part 1 crimes. The total analytic sample includes 112,314 crime reports (82.49% citizen-initiated, 17.51% officer-initiated) which are used in the analyses. By including a dummy variable for officer-initiated reports and creating an interaction term between that variable and the proportion Black, I examine how the proportion Black is related to probability of arrest for both citizen-initiated calls and officer-initiated reports to examine any differences in the exercise of police power between these two scenarios.

Limitations in Data and Missingness

While Part 1 and Part 2 crimes are both relevant to conflict theory, I only have access to arrest data for Part 1 crimes. As such, only calls and crime reports related to Part 1 crime data are included in these analyses. There is a large amount of missing data in the race and gender of the victim as provided by BPD, and this missingness is correlated with one of the main independent variables, proportion Black of the block group. Ideally, dispatch priority would be included as an additional call-level variable, but it is missing for most officer-initiated calls. The dispatch priority is the priority level assigned to a call and relayed to the responding officer by the dispatcher. This may prime officers to consider a given situation more urgent or more serious, which could impact their likelihood of using formal social control in the form of an arrest.

[7] This analytic sample also does not include calls that took place in the 10 block groups with fewer than fifty residents.

Independent Variables

To ensure the appropriate temporal ordering, the independent variables that capture neighborhood characteristics are based on the estimates from *2011-2015 American Community Survey (ACS)*. The 5-year estimates from the ACS are "period" estimates representing data collected over a period of time. The primary advantage of using multi-year estimates is the increased statistical reliability of the data for less populated areas and small population subgroups (US Census Bureau, 2023). The main neighborhood characteristics of interest are racial composition and concentrated disadvantage.

Racial Composition

Racial composition is measured at one point in time, as well as change over time. The dynamic measures of racial composition are the level change in proportion Black, and the percentage change in proportion Black, categorized as negative change, no change, or positive change. Racial composition is measured as the proportion of residents in a block group that are non-Hispanic Black, which is calculated by the number of non-Hispanic Black residents divided by the total population of a block group. This includes those who selected more than one racial category, as long as at least one of the selected categories was Black.

Changes in Racial Composition

In line with Blalock's RTT, I also include two measures of change in racial composition. First, I take the simple difference between the proportion non-Hispanic Black in the 2011-2015 estimates and the proportion non-Hispanic Black in the 2000

Census. While my static measure of racial composition comes from the ACS 5-year estimates, the baseline racial composition is measured in the 2000 Census. This simple difference was selected over percent change because of the large number of block groups that had no White/Black residents in 2000 that changed to have some number of White/Black residents in 2011-2015. These zero counts in the baseline year do not allow me to make percent change calculations[8]. However, these block groups that went from no Black population to some Black population are meaningful and theoretically important for racial threat, so I measure the change as a level change rather than a percent change.

A second measure of change in racial composition is categorical for both the Black and White population within a block group. For each block group, the percent change from 2000 to 2011-2015 is calculated for both the Black population and the White population. Then, each block group is assigned a category for change in Black population (negative change, no change, positive change), and a category for change in White population (negative change, no change, positive change). The change in White population is not simply an inverse of the change in Black population, since the change in White population excludes people of all non-White racial/ethnic groups (including Asian and Latino), while the change in the Black population only includes non-Hispanic Black people. For the same reason as above, this percent change calculation is undefined in block groups that had no residents of either racial group in

[8] The percent change formula is $\% \, \Delta = \frac{(proportion\ Black\ 2011{-}2015 - proportion\ Black\ 2000)}{Proportion\ Black\ 2000}$, and numbers cannot be divided by 0. Therefore, block groups with 0 Black residents in 2000 will have an undefined percent change.

2000. To overcome this issue, I chose to categorize percent change in this way, such that block groups that had no Black residents in 2000 but witness an increase in Black residents in 2011-2015 are assigned as having positive change in the Black population, and similarly block groups that had no White residents in 2000 and an increased number of White residents in 2011-2015 are assigned as having positive change in the White population. Since RTT relies on *perceptions* of threat, differences in racial composition must be large enough to be perceptible by residents. Small changes in racial composition are unlikely to be detected by residents, and thus would not constitute an increasing threat. Therefore, block groups with a percent change in either the Black population or White population of between -10% and +10% are coded as "no change"[9]. The number of block groups that had negative change, no change, and positive change are enumerated for both the Black population and the White population in Table 1.

Concentrated Disadvantage

The index measure of concentrated disadvantage follows prior literature (Peterson & Krivo, 2010) and is the average of the standardized scores of the following variables: the proportion of residents living below the poverty line, the proportion of households that are female-headed with children, the unemployment rate for those age 16 and older, and the proportion of residents age 25 and over that have not completed college (α=0.781). The pairwise correlations for each of the variables included in the index measure are between 0.42 and 0.62.

---

[9] For future directions, I may explore this threshold at different values.

Victim Race and Gender

In line with prior research on the relationship between victim characteristics and arrest outcomes, I include a binary variable that equals 1 for female victims (=0 for male victims) and another binary variable that equals 1 for White victims (=0 for non-White victims). These victim characteristics are theoretically relevant to BNH because police officers may view certain victims as less "deserving" of justice and therefore, less likely to make an arrest. Insofar as police officers represent the culturally dominant group in the US, they are more likely to view White victims as deserving of justice. However, White victims in majority Black neighborhoods are more likely to be perceived as being "out of place," or in a neighborhood where they don't belong. In this case, police officers may view White victims as less deserving of justice. Additionally, officers may view female victims as more deserving of justice because of notions of chivalry.

Control Variables

Crime Type

The call-level independent variables include the reported Part 1 crime type, with robbery disaggregated by type. The Part 1 crime types include: aggravated assault, arson, auto theft, burglary, homicide, larceny, larceny from auto, rape, robbery (carjacking), commercial robbery, residential robbery, street robbery, and shooting. I also include a binary variable of whether a gun was present during the commission of the crime. These call-level characteristics are important to include, since RTT and BNH predict the relationship between neighborhood racial composition and probability of arrest, assuming that neighborhoods are comparable in all other ways. However, the composition of crime types committed varies between neighborhoods, and crime types have very different associated probabilities of arrest. Therefore, I control for crime type in order to more accurately compare the probability of arrest across neighborhoods.

Police District

Finally, I account for the police district where the call takes place. Police districts are too large to meaningfully represent a neighborhood or community social area, and therefore are not employed as the level of aggregation to compute racial composition, concentrated disadvantage, or other neighborhood level dynamics. However, there may be cultural or informal policy differences in policing practice between police districts that may lead to different probabilities of arrest in different districts. Therefore, I control for police district, because I am specifically focused on neighborhood characteristics, rather than departmental or organizational differences. In Baltimore, there are nine police districts. Each district is included in the analysis as a dummy variable except for District 1, which is the reference category.

Seasonality

To account for any seasonality in the probability of arrest, I include dummy variables for each month to indicate what month the crime was reported during. In the regressions, January is the reference category.

Other Neighborhood Demographics

Informed by prior literature on neighborhoods and crime, the following neighborhood characteristics are also included as controls: total population, number of calls, proportion of population who are males aged 15-24, proportion of households who speak limited English, proportion of owner-occupied housing units with a mortgage, proportion of housing units that are vacant, and proportion of housing units that are renter occupied. The number of calls is the sum of all 911 calls for service in a block group within the study period as provided by BPD, and the rest of the neighborhood variables are from the ACS 5-year estimates for 2011-2015.

Chapter 4: Analytic Strategy

Within this study, I use multi-level modeling (MLM) to construct a series of logistic regression models to predict the probability of arrest following a Part 1 crime report. In this analysis, calls for service (Level 1) are nested within neighborhoods (Level 2), because crimes within a block group are not necessarily independent of each other (Velez et al., 2015). Furthermore, block groups potentially influence the characteristics and activities of surrounding block groups, so the Level 2 variables are likely not independent either. To remedy concerns of spatial autocorrelation between block groups, I use the solution proposed by Bester and colleagues (2011) and account for this spatial autocorrelation through the clustering of robust standard errors at the next aggregated unit, the census tract (Bester et al., 2011).

Multi-level modeling is appropriate for the dataset of calls for service nested within neighborhoods because it correctly estimates standard errors where single level regression would underestimate standard errors, incorporate information on group level relationships with an analysis of individuals, and link calls to their neighborhood context (Vogt et al., 2014). Because the current study seeks to understand how neighborhood context impacts the probability that a call will end in an arrest, MLM is an appropriate model to explore this relationship. Multi-level modeling is appropriate for studying the separate effects of level 1 and level 2 variables, in this case call-level variables and neighborhood-level variables. Multi-level modeling adjusts for the error correlation of level 1 units within level 2 units, since calls within a neighborhood are not independent of each other. Without MLM, the effects of level 2 variables will be underestimated, and the effects of level 1 variables will be overestimated (Vogt et al., 2014).

The MLM package in Stata (MP 17.0), melogit, calculates a mixed-effects model that incorporates both random effects and fixed effects where the probability that the outcome equals 1 is determined by the logistic cumulative distribution function. My multi-level model includes a random intercept for each block group. Mixed-effect models properly account for the correlation between units nested within the same group.

Regression Models

All models include total block group population and number of calls as controls, as well as the neighborhood demographic control variables (proportion male age 15-24, proportion with a mortgage, proportion limited English, proportion vacant housing units, and proportion renter occupied housing units), crime type (larceny from auto is the reference group), presence of a gun, district (District 1 is the reference group), and month (January is the reference group). Additionally, all models include a binary variable that equals one for calls that are officer-initiated.

The baseline model (Model 1) predicts the probability of arrest using the static proportion Black. The results from Model 1 and Model 2 are presented in Table 4. Model 2 includes an interaction between the binary variable indicating an officer-initiated report and the proportion Black to test if the relationship between racial composition and probability of arrest differs between citizen-initiated and officer-initiated calls. This interaction term is included in all subsequent regressions. The next set of regressions include measures of change in racial composition in addition to the static measure of proportion Black. Table 5 presents results for Models 3 and 4, which include two different dynamic measures of racial composition. Model 3 uses the level change in proportion Black as the primary dynamic measure of racial threat. Model 4 uses the categorical measures of percent change in proportion Black where the reference group is no change in the proportion Black.

The next stage of analysis provides an initial investigation into the relationship between neighborhood characteristics and the probability of arrest after controlling for victim race and gender. The next two models use a reduced sample since many observations are missing information on victim race and/or gender. Thus, only calls with information on victim race *and* gender are included in Models 5 and 6. Because of the missing data on victim characteristics, these models are not considered the main analysis. Table 6 presents the results from Model 5 and Model 6. Model 5 is the baseline model from above, with the binary variables for female victim and White victim. Model 6 includes the binary variables for female victim and White victim, as well as the level change in proportion Black as a dynamic measure of threat.

Chapter 5: Results

Descriptive Statistics

Panel A: Call-Level Characteristics

Part 1 crime types. The proportion of each Part 1 crime type varies between neighborhoods. Additionally, the probability of arrest varies by crime type. Therefore, to truly understand how neighborhood characteristics are related to the probability of arrest, we need to consider how much of the variability in arrest rates between neighborhoods is due to differences in crime types.

Of the 112,314 calls that resulted in a Part 1 crime report city-wide, 92,649 (82.49%) were citizen-initiated and 19,665 (17.51%) were officer-initiated calls. The number of calls varied across crime types (Table 2, *Panel A*). Larceny accounted for the largest number of calls (*n*=29,204) and arson for the fewest (*n*=621). The proportion of calls for each Part 1 crime type also varied across block groups. For example, larceny accounted for as much as 83.94% of calls in one block group, and as few as 5.88% of calls in another (*m*=23.85, *sd*=9.60). Table 1 in Appendix B provides more detail (mean counts and proportions) on crime types city-wide, disaggregated by citizen-initiated and officer-initiated calls. Tables 2 and 3 in Appendix B provide more detail (mean counts and proportions) on the variation in crime type between block groups disaggregated by citizen-initiated and officer-initiated calls.

There were 8,102 (8.74%) arrests made as a result of citizen-initiated calls, and 1,721 (8.75%) arrests made as a result of officer-initiated calls. The percentage of calls that ends in arrest varies between 1.48% for larcenies from an automobile to

40.06% for residential robberies. See Appendix B, Table 4 for additional detail on the city-wide probability that an arrest will be made following a Part 1 crime report. The average block group had 12.60 arrests that resulted from a citizen-initiated call, and 2.68 that resulted from an officer-initiated report, totaling an average of 15.28 arrests (for more information see Appendix B, Table 5). For the average block group, the highest probability of arrest was for residential robbery (*m*=28.08%, *sd*=35.89, range=0-100) and the lowest was for larceny from auto (*m*=1.21%, *sd*=2.47, range=0-16.67). See Appendix B, Table 6 for additional detail.

Call and Victim Characteristics. On average, each block group had 17.38 (*sd*=14.70, range=0-162) calls for a crime in which a gun was present. On average, 9.84% (*sd*=4.42%, range=0-23.15%) of calls in a block group had a gun present. Citizen-initiated calls were significantly more ($p<.01$) likely to be about crimes in which a gun was present, 10.33% (*sd*=4.64, range=0-26.56) compared to officer-initiated 7.58% (*sd*=7.20, range=0-46.67).

Of the 85,068 calls for which data on victim's sex were available, 44,950 (48.14%) were those with a female victim. These rates were similar across citizen-initiated (*m*=48.79%, *sd*=7.86) and officer-initiated calls (*m*=48.93%, *sd*=14.35). Of the 76,885 calls for which data on victim's race were available, 24,854 or 38.65% of calls were those with a White victim. At the average block group, 38.65 or 32.13% of calls were those involving White victims. Block group averages of citizen-initiated calls about White victims occurred slightly less than officer-initiated calls about White victims, 31.75% (*sd*=29.90) and 33.82% (*sd*=29.87) respectively. This difference is significant at $p<.01$. See Appendix B, Tables 7 through 9 for more detail.

In summary, both counts and percentages of calls about Part 1 crimes, as well as arrests following those calls, significantly vary by block groups in Baltimore. In most cases, the frequency and rates are consistent between citizen- and officer-initiated calls, with some notable differences (e.g., presence of a gun, White victim). The distribution of call-level characteristics is varied, as are the neighborhood-level (block group) characteristics, across the city.

Panel B: Block Group-Level Characteristics

Panel B of Table 2 presents the neighborhood characteristics of block groups. The average number of residents in a block group is 958.80 (*sd*=500.30), although it ranges from 95 to 3,828. The average disadvantage index score is 0.004 (*sd*=0.78). The average proportion of residents living below the poverty line is 0.25 (*sd*=0.17). The average proportion of residents who are unemployed is 0.15 (*sd*=0.12). The average proportion of residents who have no college education is 0.69 (*sd*=0.24). The average proportion of households that are female-led and have children is 0.25 (*sd*=0.17). The average proportion of non-Hispanic Black residents is 0.67 (*sd*=0.35), and 60.80% of block groups are considered a Black neighborhood, where more than 70% of the residents are Black. These neighborhood characteristics vary greatly between block groups, highlighting the high levels of segregation.

Baseline Model

The baseline model is constructed in steps, where each "level" of predictor variables is added sequentially to the model. Table 3 presents the results of this sequential process. First, I estimate an unconditional mean model that includes no independent variables. The intra-class correlation (ICC) of the unconditional mean model is 0.026, which means that 2.6% of the variance in the probability of arrest can be attributed to block group-level factors, and more than 97% of the variance comes from level 1 dynamics. Next, I add the Level 1 predictor variables, or the variables related to the call/crime report. The likelihood-ratio test confirms that adding the Level 1 predictors adds significant explanatory power to the model ($\chi^2 = 9744.07$, *p*<.01). Next, I add the Level 2 (block group) predictor variables. The likelihood-ratio test confirms that adding the Level 2 predictors adds significant explanatory power to the model ($\chi^2 = 51.81$, *p*<.01). Finally, I add in the police district dummy variables. Using the likelihood-ratio test, the district variables only add significant explanatory power at the 10% significance level ($\chi^2 = 13.60$, *p*=0.093). In the final model, the ICC is 0.016, which means that after accounting for the included variables, 1.6% of the variance in the probability of arrest can be attributed to the block group where the crime was reported. The final model is used for all future model specifications.

The results from the baseline multi-level logistic regression are presented below in Table 4. The coefficient estimates are presented as odds ratios, which is the ratio of the odds of the outcome happening (in this case, arrest) to the odds of the outcome not happening (no arrest). When the odds ratio is less than one, it means an arrest is less likely to occur, while an odds ratio that is greater than one indicates that an arrest is more likely to occur. The odds-ratios presented in the tables are then converted to average marginal effects by finding the difference between two probabilities as predicted by the odds ratio and dividing by the base rate of arrest. In both models 1 and 2, the proportion of residents who are Black is significantly and negatively associated with the probability of arrest. In the baseline model, the average marginal effect of a one unit increase in proportion Black is a decrease in the probability of arrest by 0.02, or 20.30%. This negative relationship is illustrated in Figure 1, which shows the marginal predicted probability of arrest at different proportions of Black residents, averaged over all observations. However, this is not particularly realistic, as this means the probability of arrest is 20.30% lower in a neighborhood that is 100% Black than in a neighborhood that is 0% Black. While comparing the probability of arrest for the same crime in a totally White neighborhood compared to a totally Black neighborhood is interesting, most neighborhoods are not this extreme. Therefore, looking at small changes in the neighborhood proportion Black is potentially more meaningful and reflective of most neighborhoods in Baltimore. Specifically, a ten-percentage point increase in proportion Black from the mean is associated with a 2.01% reduction in the probability of arrest. Similarly, a ten-percentage point decrease in proportion Black from the mean is associated with a 2.04% higher probability of arrest. As expected, officer-initiated calls have a higher probability of ending in an arrest than citizen-initiated calls. The average marginal effect of a call being officer-initiated over citizen-initiated is an increased probability of arrest by 0.02, or 17.32%. This difference is illustrated in Figure 2. Surprisingly, disadvantage is not significantly related to the probability of arrest[10]. The type of Part 1 crime and the presence of a gun are also significantly related to the probability of arrest.

Model 2 includes an interaction between the officer-initiated binary variable and the proportion Black to test if the relationship between proportion Black and the probability of arrest differs between citizen-initiated and officer-initiated calls. This interaction is not statistically significant in Model 2, which indicates whether a call is citizen-initiated or officer-initiated does not moderate the relationship between proportion Black and the probability of arrest. This interaction is illustrated in Figure 3. In other words, the relationship between proportion Black and the probability of arrest is not significantly different between officer-initiated calls and citizen-initiated calls. This indicates that officer perceptions of racial threat, and therefore the need for formal social control, are consistent regardless of who initiates the interaction. In Model 2, the average marginal effect of a one unit increase in proportion Black is a decrease in the probability of arrest by 0.02, or 20.30%. The probability of arrest is 20.30% lower in an all-Black neighborhood compared to an all-White neighborhood, and where a ten-percentage point increase in proportion Black from the mean is associated with a 2.04% reduction in the probability of arrest. Similarly, a ten-percentage point decrease in proportion Black from the mean is associated with a 2.07% higher probability of arrest. Officer-initiated calls have a higher probability of ending in an arrest, such that the average marginal effect of a call being officer-

[10] The significance of disadvantage does not change in any of the following model specifications. Additionally, when disadvantage is in the model without proportion Black, it is still insignificant. This is evidence that the non-significance of disadvantage is not simply a statistical artifact of proportion Black and disadvantage being highly correlated.

initiated over citizen-initiated is an increased probability of arrest by 0.02, or 17.28%. Disadvantage remains insignificant. The type of Part 1 crime and the presence of a gun are also significantly related to the probability of arrest.

Racial Composition Change

Level Change

The results from the multi-level logistic regression that includes the change in proportion Black from 2000 to 2011-2015 (Model 3) are presented below in Table 5. The coefficient estimates are presented as odds ratios. The proportion of residents who are Black is significantly associated with the probability of arrest. The average marginal effect of a one unit increase in proportion Black is a decrease in the probability of arrest by 0.02, or 20.67%. The probability of arrest is 20.67% lower in an all-Black neighborhood compared to an all-White neighborhood, and where a ten-percentage point increase in proportion Black from the mean is associated with a 1.99% reduction in the probability of arrest. Similarly, a ten-percentage point decrease in proportion Black from the mean is associated with a 2.02% higher probability of arrest. Change in proportion Black is not significantly related to the probability of arrest. Officer generated calls have a higher probability of ending in an arrest, but the relationship between proportion Black and the probability of arrest is not significantly different between citizen-initiated calls and officer-initiated calls. As in Model 1, disadvantage is not statistically significant.

Categorical Change

The results from the multi-level logistic regression that includes the categorized percent change in proportion Black from 2000 to 2011-2015 (Model 4) are presented below in Table 5. The categorized percent change in proportion Black examines the effect of percent change in proportion Black, rather than the simple level-change as above. The coefficient estimates are presented as odds ratios. The proportion of residents who are Black is significantly associated with the probability of arrest. The average marginal effect of a one unit increase in proportion Black is a decrease in the probability of arrest by 0.02, or 19.68%. The probability of arrest is 19.68% lower in an all-Black neighborhood compared to an all-White neighborhood, and where a ten-percentage point increase in proportion Black from the mean is associated with a 1.94% reduction in the probability of arrest. Similarly, a ten-percentage point decrease in proportion Black from the mean is associated with a 1.98% higher probability of arrest. Relative to no change, a neighborhood having a positive or negative change in the proportion of the population that is Black is not significant. Police generated calls have a higher probability of ending in an arrest, but the relationship between proportion Black and the probability of arrest is not significantly different between citizen-initiated calls and officer-initiated calls. As above, disadvantage is not significantly related to the probability of arrest.

Race and Gender of Victim

Baseline Model

The next two models, Model 5 and Model 6, include victim characteristics (gender and race) as controls, since the relationship between racial composition and the probability of arrest may differ by the race of the victim. Further, the victim's gender may also impact the probability of arrest. The results from the multi-level logistic regression that includes a binary for female victim and for White victim are presented in Table 6. The coefficient estimates are presented as odds ratios. The proportion of residents who are Black is significantly associated with the probability of arrest. The average marginal effect of a one unit increase in proportion Black is a decrease in the probability of arrest by 0.02, or 25.35%. The probability of arrest is 25.35% lower in an all-Black neighborhood compared to an all-White neighborhood, and where a ten-percentage point increase in proportion Black from the mean is associated with a 2.52% reduction in the probability of arrest. Similarly, a ten-percentage point decrease in proportion Black from the mean is associated with a 2.57% higher probability of arrest. Crimes where the victim is female have a higher probability of ending in an arrest. On average, the victim being female is associated with a 24.91% higher probability of arrest. This relationship is illustrated at different levels of proportion Black in Figure 4. On average, the victim being White is associated with a 6.64% reduction in the probability of arrest. This relationship is illustrated at different levels of proportion Black in Figure 5. Police generated calls have a higher probability of ending in an arrest, but the relationship between proportion Black and the probability of arrest is not significantly different between citizen-initiated calls and officer-initiated calls. Again, disadvantage is not statistically significant.

Level Change

The results from the multi-level logistic regression that includes a binary for female victim and for White victim and the change in proportion Black from 2000 to 2011-2015 are presented in Table 6. The coefficient estimates are presented as odds ratios. The proportion of residents who are Black is significantly associated with the probability of arrest. The average marginal effect of a one unit increase in proportion Black is a decrease in the probability of arrest by 0.02, or 25.31%. The probability of arrest is 25.31% lower in an all-Black neighborhood compared to an all-White neighborhood, and where a ten-percentage point increase in proportion Black from the mean is associated with a 2.51% reduction in the probability of arrest. Similarly, a ten-percentage point decrease in proportion Black from the mean is associated with a 2.56% higher probability of arrest. Change in proportion Black is not related to the probability of arrest. Crimes where the victim is female have a higher probability of ending in an arrest. On average, the victim being female is associated with a 24.90% higher probability of arrest. On average, the victim being White is associated with a 6.95% reduction in the probability of arrest. Officer-initiated calls have a higher probability of ending in an arrest, but the relationship between proportion Black and the probability of arrest is not significantly different between citizen-initiated calls and officer-initiated calls. As with all previous models, disadvantage is not significantly related to the probability of arrest.

Non-Linear Measures of Racial Composition

I also explore non-linear measures of racial composition. The results of this exploration are presented in Appendix C. First, I add an interaction term between proportion Black and the disadvantage index, which is insignificant (see Model 1). Second, I then try a squared term of proportion Black, which is also insignificant (see Model 2). I categorize proportion Black into quartiles and find that the second, third, and fourth quartiles are all associated with significantly different odds ratio of arrest, when compared to the first quartile. Similarly, in Model 4, proportion Black is categorized by deciles of the data. All but the second decile are associated with significantly different odds of arrest when compared to calls that were in the first decile of neighborhood proportion Black. Further, the odds ratio declines for all deciles, although the differences between deciles are larger at lower deciles of proportion Black. It seems that the relationship between proportion Black and the probability of arrest is more steeply negative at lower values of proportion Black, but steadily declining across all values. This is illustrated in Figure 6, which shows the marginal predicted probability of arrest for each quartile of proportion Black. This relationship is negative, with a steeper slope between the first two quartiles than for the rest of the quartiles. Similarly, Figure 7 shows the marginal predicted probability of arrest for each decile of proportion Black. This relationship is also negative, with the steepest slopes at lower deciles of proportion black. This relationship can also be seen in Appendix C, Table 1, as the difference between odds-ratios declines as the decile/quartile increases. I primarily focus on the overall negative relationship in the following discussion, although there is evidence that the exact functional form between proportion Black and the probability of arrest may be non-linear. I return to this possibility briefly in the next chapter.

Chapter 6: Discussion and Conclusion

Current Study

The past decade has brought a new wave of protests against the police, specifically against perceived racially disparate policing practices (Brunson, 2020; Donovan, 2015). Within Baltimore, the pattern of racial disparities in arrest outcomes was highlighted by the DOJ investigation following Freddie Gray's death (Investigation of the Baltimore City Police Department, 2016). The use of formal social control, including through arrests, has important consequences for the individuals arrested (Beardslee et al., 2019; Uggen et al., 2014), as well as long-term impacts on police-community relationships (Boehme et al., 2022; Weitzer et al., 2008). Given the practical impact of arrests, and because police behavior is situated within neighborhood contexts, it is important to study how neighborhood characteristics are related to the probability of arrest. Within the conflict tradition, both RTT and the BNH have been used to predict the relationship between neighborhood racial composition and concentrated disadvantage and the use of formal social control. The current study builds on the extant literature testing both theories by specifically testing them in the context of Baltimore, a majority-minority city. Conflict theories have been understudied in contexts where White people are not the numeric majority; despite the fact that these contexts are becoming increasingly common as the United States continues to diversify and become increasingly less White. Additionally, the present study separately investigates the impact of neighborhood context by citizen-initiated and officer-initiated calls, as police officers employ social control measures differently within these two contexts. Finally, the present study includes both dynamic and static measures of racial threat in a multi-level model to understand the relationship between neighborhood racial composition and concentrated disadvantage, and police officer use of social control in the form of arrests.

The results of this study are consistent with the BNH, in that the proportion of residents who are Black in a block group is negatively associated with the probability of arrest. In other words, the probability of a call resulting in an arrest is lower in block groups with higher proportions of Black residents, all else equal. The BNH predicts this negative relationship, but it also predicts this negative relationship for other marginalized groups, such as neighborhoods with high levels of disadvantage. Surprisingly, the level of disadvantage is not significantly associated with the probability of arrest following a Part 1 crime report in Baltimore, regardless of model specification. When disadvantage is included in models without proportion Black[11], it remains insignificant, which is evidence that the finding of disadvantage as not significant is not solely due to the high correlation between proportion Black and disadvantage. As expected, the type of crime is significantly related to the probability of arrest (p<.01). Additionally, the use of a gun in the commission of the crime is associated with a higher probability of arrest (p<.01).

The current proportion Black is negatively associated with the probability of arrest, regardless of how it has changed over time. While much of the extant racial

[11] These models are not presented in this paper but can be provided upon request.

threat literature has used only a static measure of racial composition as a proxy for threat, increasingly, and consistent with Blalock's RTT, there have been calls to include a dynamic measure of the *change* in racial composition over time. This study does include dynamic measures of racial threat (presented in Table 5). The change in proportion Black from 2000 to 2011-2015 is included in the regression results that are presented in Table 5, Model 3. Table 5, Model 4 presents the results of the regression that includes percent change in proportion Black categorized as negative change, no change, or positive change in the Black population. None of the dynamic measures of threat are significantly related to the probability of arrest, and it does not alter the relationship between static proportion Black and probability of arrest. This is consistent with BNH, which unlike RTT, does not make any claims about the *change* in racial composition over time. This finding conflicts with Parker and colleagues (2005), who also found support for BNH and that the percent change in Black immigration was also negatively associated with arrest rates. However, Black immigration is only one way that the proportion of Black residents can change over time in a location. For example, changes in proportion Black may also reflect higher birth rates among Black residents or White out-migration. The difference in finding may be due to Parker and colleagues only including Black immigration in their dynamic measure of threat, while I consider overall changes in the proportion of the population that is Black.

There are several possible reasons that explain why I do not find support for RTT in Baltimore. First, I study arrest probabilities from 2016-2018, which is in the wake of Freddie Gray's death and subsequent protests and DOJ investigation. There is evidence of de-policing in Baltimore following Freddie Gray's death (Midgette & LaFree, forthcoming). If this de-policing occurred more intensely in majority Black neighborhoods, this would produce the observed lower probability of arrest in these neighborhoods. Thus, it is possible that in other historical contexts in Baltimore, there would be support for RTT. Second, RTT may not be applicable in majority-Black places. As previously mentioned, RTT has primarily been tested in majority-White places, and the one other identified study of RTT and arrest probabilities in a majority-Black city also found support for BNH over RTT (Kane et al., 2013).

Prior literature has also emphasized the importance of victim characteristics related to outcomes of police encounters. In this study, two binary variables are included in the regression (see Table 6), one that equals 1 when the victim was female and one that equals 1 when the victim was White. However, there is a significant amount of missingness in the recording of both victim race and gender, so this regression uses a limited sample size of observations that have both victim gender and race recorded (N=76,521). The proportion of calls for which victim gender and race were and were not recorded that end in arrest is not substantially different (0.09 vs. 0.08). However, the proportion of calls for which victim gender and race were and were not recorded does differ by average proportion of block group residents that are Black (0.65 vs. 0.56). In other words, a smaller proportion of calls included data on victim gender and race in block groups with smaller proportions of Black residents. Using this subsample and including whether the victim was female or White, the magnitude of the negative association between proportion Black and probability of arrest is larger. The victim being female is positively associated with the probability of arrest, while the victim being White is negatively associated with the probability of arrest. Figure 4 shows the predicted marginal probability of arrest by neighborhood proportion Black, comparing female victims and male victims for both citizen-initiated and officer-initiated calls. Figure 5 shows the predicted marginal probability of arrest by neighborhood proportion Black, comparing White victims and non-White victims for both citizen-initiated and officer-initiated calls.

Alternative Explanations

Recall that a key finding from the current study is that the neighborhood proportion Black is negatively associated with the probability of an arrest after a Part 1 crime report. While I frame this finding as support for the benign neglect hypothesis, there are other possible pathways to explain this relationship. The proportion Black maintains a negative relationship with the probability of arrest net of key controls, which suggests a residual race effect on arrest. This may mean that other factors related to police officer perceptions are correlated with proportion Black. For example, one reason police may be less likely to make an arrest in a neighborhood with a higher proportion of Black residents is because they view victims in those neighborhoods as "less deserving" of justice, or they may view more serious offenses as "normal deviance" in neighborhoods with a higher proportion of Black residents. Klinger (1997) proposed an ecological theory of police responses based on perceptions of deviance at the police district level. He theorized that police district work group norms are framed by district-level workload, police cynicism, normal and deviant deviance, and the deservedness of victims. Although I attempt to control for differences in police district work norms by controlling for the district that each call takes place in, it is also possible that these factors shape police behavior at smaller units of analysis. I have controlled for the number of calls made in each block group as a proxy for the police workload. However, Klinger's ecological theory is based on officer *perceptions* of deviance levels, which may differ from actual levels of crime reports. Although I have no measures of police cynicism, perceptions of kinds of deviance as normal or deviant, or the deservedness of victims, these factors do not necessarily conflict with benign neglect.

If situational factors that are associated with arrest are differentially distributed in neighborhoods in a way that is correlated with the racial composition of the neighborhood, these situation-level factors may be contributing to my findings. The residual race effect may reflect unmeasured situational factors that are likely to be correlated with neighborhood racial composition. Black (1971) proposed a theory that includes the following situation-level factors that impact the probability of an arrest: suspect race, legal seriousness of the alleged crime, evidence available in the field setting, complainant's preference for police action, social relationship between complainant and suspect, suspect's degree of deference toward the police, and manner in which the police come to handle an incident. In other words, the probability of arrest may be lower in neighborhoods with a higher proportion of Black residents for reasons unrelated to the racial composition, but because of the distribution of other factors that police use in their decision to arrest. For instance, neighborhoods with a higher proportion of Black residents may be less likely to have residents who request that police respond with arrest. In other words, crimes in neighborhoods with a higher proportion of Black residents may be more likely to have specific situational factors that are less likely to yield an arrest.

Implications

The results of this study have important implications for theory and policy. Theoretically, this study advances the literature testing RTT, and finds that RTT is not supported in a highly segregated, majority-Black city. This is important because conflict theories, including RTT, have primarily been tested nationally or in majority-White cities. However, as the US becomes increasingly diverse and non-White, it is important to consider how these theories operate in places that are not majority-White. Specifically, this study adds to our understanding of how racialized power structures are operating under changing racial demographics in the US.

Methodologically, this study adds to the prior literature by including a dynamic measure of threat in addition to a static measure of threat, and by employing multi-level modeling. Although I do not find the dynamic measure of threat to be significantly associated with the probability of arrest, it is theoretically important to include in tests of RTT, since Blalock's RTT emphasizes the importance of change over time, not just the static racial composition. This study highlights the importance of utilizing multi-level modeling in tests of community-level theories. I find significant relationships between the crime type, presence of a gun, and female victim and the probability of arrest. Without including these call-level characteristics, my model of neighborhood effects would be mis-specified.

The findings of this study also have practical implications for policing practices, especially in majority-Black cities. Specifically, I highlight the importance of combatting underpolicing in marginalized communities, although much of the popular critiques of policing in these communities focuses on overpolicing. Although the magnitude of the difference in probability of arrest is not large, the real-world impact is significant. In an average block group, a ten-percentage point difference in proportion Black is associated with about one fewer arrests made. Considering there are 643 block groups with at least fifty residents in Baltimore, this amounts to a potential difference of about 650 arrests over a three-year period, due only to neighborhood characteristics. This is a substantial effect if we believe that extra-legal characteristics, such as neighborhood racial composition, should have *no* effect on criminal justice outcomes, including arrests.

Limitations and Future Research

Although this study moves the field forward in several important ways, it is not without limitations. The first set of limitations is related to the data available from the Baltimore Police Department. First, I did not have access to data that has information on suspect gender or race. The effect of neighborhood composition on the probability of arrest may vary by suspect race. For example, the probability of an arrest in a majority White neighborhood might be higher for a Black suspect, but not for a White suspect. However, I am not able to parse this out using the available data. Although the data does include victim gender and race, there is a good bit of missingness in these variables, and this missingness is correlated with one of the main independent variables, proportion of the block group's residents that are Black. The data also does not include additional situational or officer level characteristics that may be theoretically or empirically important when examining probability of arrest. Additionally, we might expect that extralegal factors, such as neighborhood racial composition, have a greater impact on the probability of arrest for situations where police officers have more discretion. Police officers are likely to have more discretion for minor crimes and violations, but unfortunately, I only have access to arrest data for Part 1 crimes, for which discretion might be limited. This means that my findings are likely a conservative estimate of the relationship between neighborhood characteristics and arrest probabilities. In order to investigate the true magnitude of the relationship between neighborhood racial composition and the probability of arrest, future studies including suspect characteristics are vital.

For the future directions of this study, I could explore alternative measures of crime type to check the robustness of these findings. For example, I could control for how the call is coded by the dispatcher (dispatched incident code) or by the responding officer (returned incident code) instead of how the crime is finally reported by the officer. Although preliminary explorations are consistent with the current findings, I could more deeply explore nonlinear forms of proportion Black and disadvantage, including squared terms, interaction terms, or binned categories rather than a continuous measure.

This study also introduces several questions to be further researched. First, my findings in support of BNH may be an artifact of the study time period. There is evidence of de-policing in Baltimore following the death of Freddie Gray and the subsequent protests (Midgette & LaFree, forthcoming). It is possible that this de-policing occurred more in neighborhoods that have a higher proportion of Black residents, since the police-community relationship is most tense in these neighborhoods (Peck & Elligson, 2021), as a way to reduce the likelihood of being involved in the next high-profile case that may spark controversy. A future study might investigate the relationship between neighborhood characteristics and the probability of arrest both before and after the death of Freddie Gray. Additionally, the de-policing effect might be relatively temporary. Thus, a future study could investigate this relationship immediately following the death of Freddie Gray, and subsequently several years after.

This study finds support for BNH in the context of a majority-Black city that is highly segregated. It is possible that cities with less segregation may exhibit a relationship that is more consistent with RTT. The present study is unable to make claims about the impact of segregation on the relationship between proportion Black and the probability of arrest, as it only uses data from one city. However, a future study may compare many cities with varying amounts of residential segregation to see how this relationship changes with amount of segregation.

Conclusion

Utilizing citizen-initiated and officer-initiated 911 calls for service and Part 1 Crime reports, I conducted a multi-level test of RTT and BNH, including both static and dynamic measures of racial threat. I find support for BNH over RTT, since the proportion of residents who are Black is negatively related to the probability of arrest. This study advances the prior literature by focusing on a majority-Black city that is highly segregated. Additionally, I distinguish between citizen-initiated and officer-initiated interactions, which represent theoretically different relationships between the police and residents, and find that officer-initiated interactions are more likely to end in arrest, regardless of the neighborhood proportion Black.

The results of this study indicate that in addition to other important outcomes, neighborhood characteristics also shape criminal justice outcomes, including the probability of arrest. In Baltimore, residents in majority Black neighborhoods are being underserved by police officers as illustrated by a lower probability of arrest following both citizen- and officer-initiated calls, which could mean that crime victims are less likely to receive justice in these neighborhoods. Residents feeling unprotected by police officers exacerbates already tense police-community relationships in minority neighborhoods, all of which highlight that this neglect is anything but benign.

Appendices

Tables and Figures

Table 1. Block groups with Negative, No, and Positive Percent Change in Proportion Black and Proportion White

		Change in Proportion Black		Change in Proportion White	
		n	%	*n*	%
Direction of Change	Negative Change	119	18.51	371	57.70
	No Change	328	51.01	103	16.02
	Positive Change	196	30.08	169	26.28
Total		643	100	643	100

Table 2. Descriptive Characteristics for Level 1 Variables and Level 2 Variables

Variables	*N*	*n*	%	*Min*	*Max*
Panel A. Call Characteristics					
Officer-initiated	112,314	19,665	17.51	0	1
Arrest made	112,314	9,823	8.75	0	1
Aggravated assault	112,314	12,314	10.96	0	1
Arson	112,314	621	0.55	0	1
Auto theft	112,314	12,952	11.53	0	1
Burglary	112,314	21,497	19.14	0	1
Homicide	112,314	948	0.84	0	1
Larceny	112,314	29,204	26.00	0	1
Larceny from Auto	112,314	17,226	15.34	0	1
Rape	112,314	972	0.87	0	1
Robbery - Carjacking	112,314	1,272	1.13	0	1
Robbery - Commercial	112,314	2,602	2.32	0	1
Robbery - Residential	112,314	1,373	1.22	0	1
Robbery- Street	112,314	9,828	8.75	0	1
Shooting	112,314	1,505	1.34	0	1
Presence of a gun	112,314	11,148	9.93	0	1
Female Victim	85,068	44,950	48.14	0	1
White Victim	76,885	24,854	32.33	0	1
Panel B. Block Group Characteristics	*N*	*Mean*	*SD*	*Min*	*Max*
Proportion Males 15-24	643	0.064	0.051	0	0.423
Proportion with a Mortgage	643	0.649	0.228	0	1
Proportion Limited English	643	0.020	0.047	0	0.383
Proportion Vacant	643	0.194	0.148	0	0.663
Proportion Renter-Occupied	643	0.508	0.250	0	1

Proportion Black	643	0.668	0.347	0	1
Proportion Latino	643	0.046	0.086	0	0.787
Disadvantage	643	0.004	0.782	-1.745	2.538
Proportion in Poverty	643	0.246	0.172	0	0.867
Unemployment Rate	643	0.148	0.115	0	0.742
Proportion no college	643	0.690	0.235	0	1
Proportion Female headed with children	643	0.247	0.174	0	1
Negative % Change in Black Proportion	643	0.185	0.389	0	1
No % Change in Black Proportion	643	0.509	0.500	0	1
Positive % Change in Black Proportion	643	0.306	0.461	0	1
Change in Proportion Black	643	0.023	0.139	-1	0.519

N=Total observations, *n*=number of calls, *SD*=standard deviation

Table 3. Building the Baseline Model

	Unconditional Mean Model		With Level 1		With Levels 1 & 2		Full Baseline Model	
	B (Odds Ratio)	*SE*	*B (Odds Ratio)*	*SE*	*B (Odds Ratio)*	*SE*	*B (Odds Ratio)*	*SE*
Total Population					1.000	(3.27e-05)	1.000	(3.28e-05)
Number of Calls					1.000	(1.63e-04)	1.000	(1.75e-04)
Proportion Black					0.787***	(0.058)	0.772***	(0.062)
Officer-initiated			1.222***	(0.055)	1.220***	(0.055)	1.220***	(0.055)
Disadvantage Index					1.040	(0.036)	1.032	(0.036)
Proportion Males 15-24					1.469	(0.589)	1.546	(0.591)
Proportion with a Mortgage					1.059	(0.081)	1.040	(0.081)
Proportion Latino					1.024	(0.235)	1.070	(0.262)
Proportion Limited English					0.498	(0.206)	0.514	(0.210)
Proportion Vacant					1.237	(0.172)	1.237	(0.183)
Proportion Renter Occupied					1.207*	(0.102)	1.252*	(0.112)
Aggravated assault [a]			29.193***	(2.144)	29.205***	(2.143)	29.099***	(2.137)
Arson [a]			5.737***	(1.017)	5.822***	(1.032)	5.792***	(1.026)
Auto theft [a]			2.757***	(0.239)	2.797***	(0.241)	2.791***	(0.241)
Burglary [a]			3.383***	(0.256)	3.412***	(0.258)	3.405***	(0.258)
Homicide [a]			58.942***	(6.441)	59.000***	(6.480)	58.872***	(6.472)
Larceny [a]			3.227***	(0.318)	3.218***	(0.313)	3.212***	(0.312)
Rape [a]			19.220***	(2.435)	19.241***	(2.448)	19.150***	(2.433)

Robbery – Carjacking [a]			22.252***	(2.523)	22.300***	(2.508)	22.333***	(2.519)
Robbery – Commercial [a]			23.182***	(1.940)	22.921***	(1.914)	22.842***	(1.904)
Robbery – Residential [a]			56.806***	(5.547)	57.247***	(5.565)	56.895***	(5.528)
Robbery – Street [a]			15.160***	(1.161)	15.053***	(1.151)	15.009***	(1.147)
Shooting [a]			9.585***	(1.407)	9.550***	(1.401)	9.510***	(1.400)
Presence of a Gun			0.437***	(0.019)	0.441***	(0.019)	0.440***	(0.019)
February [b]			1.123*	(0.060)	1.123*	(0.060)	1.123*	(0.060)
March [b]			1.059	(0.062)	1.060	(0.063)	1.060	(0.063)
April [b]			0.895*	(0.049)	0.894*	(0.049)	0.894*	(0.049)
May [b]			0.771***	(0.041)	0.770***	(0.041)	0.770***	(0.040)
June [b]			0.822***	(0.043)	0.820***	(0.043)	0.820***	(0.043)
July [b]			0.896	(0.051)	0.894	(0.051)	0.894*	(0.051)
August [b]			0.784***	(0.046)	0.782***	(0.046)	0.782***	(0.046)
September [b]			0.827***	(0.045)	0.825***	(0.044)	0.825***	(0.044)
October [b]			0.776***	(0.043)	0.774***	(0.043)	0.775***	(0.043)
November [b]			0.748***	(0.042)	0.747***	(0.042)	0.748***	(0.042)
December [b]			0.816***	(0.048)	0.816***	(0.048)	0.816***	(0.048)
District 2[c]							1.008	(0.075)
District 3[c]							1.157	(0.094)
District 4[c]							1.154	(0.095)
District 5[c]							1.078	(0.079)
District 6[c]							0.965	(0.078)
District 7[c]							1.079	(0.093)
District 8[c]							1.125	(0.089)
District 9[c]							1.074	(0.084)
Level 2 Variance	0.089	(0.012)	0.063	(0.011)	0.054	(0.010)	0.053	(0.009)
Constant	0.088***	(0.002)	0.015***	(0.001)	0.014***	(0.002)	0.013***	(0.002)

Log Pseudo-likelihood	-33,148.35	-28,276.313	-28,250.409	-28,243.610
Observations	112,314			
Number of groups	643			

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05
[a] Larceny from Auto is reference group
[b] January is reference group
[c] District 1 is reference group
SE=Robust standard errors clustered at the census tract

Table 4. Baseline Regression of Crime and Neighborhood Characteristics on Probability of Arrest

	Model 1		Model 2	
	B (Odds Ratio)	*SE*	*B (Odds Ratio)*	*SE*
Total Population	1.000	(3.28e-05)	1.000	(3.26e-05)
Number of Calls	1.000	(1.75e-04)	1.000	(1.76e-04)
Proportion Black	0.772***	(0.062)	0.784**	(0.065)
Officer-initiated	1.220***	(0.055)	1.286*	(0.143)
Officer-initiated x Proportion Black	…	…	0.920	(0.124)
Disadvantage Index	1.032	(0.036)	1.032	(0.036)
Proportion Males 15-24	1.546	(0.591)	1.546	(0.591)
Proportion with a Mortgage	1.040	(0.081)	1.039	(0.081)
Proportion Latino	1.070	(0.262)	1.072	(0.263)
Proportion Limited English	0.514	(0.210)	0.515	(0.211)
Proportion Vacant	1.237	(0.183)	1.236	(0.183)
Proportion Renter Occupied	1.252*	(0.112)	1.252*	(0.112)
Aggravated assault [a]	29.099***	(2.137)	29.135***	(2.135)
Arson [a]	5.792***	(1.026)	5.844***	(1.027)
Auto theft [a]	2.791***	(0.241)	2.799***	(0.242)
Burglary [a]	3.405***	(0.258)	3.411***	(0.260)
Homicide [a]	58.872***	(6.472)	58.922***	(6.485)
Larceny [a]	3.212***	(0.312)	3.216***	(0.312)
Rape [a]	19.150***	(2.433)	19.197***	(2.413)
Robbery – Carjacking [a]	22.333***	(2.519)	22.381***	(2.518)
Robbery – Commercial [a]	22.842***	(1.904)	22.907***	(1.932)
Robbery – Residential [a]	56.895***	(5.528)	56.941***	(5.533)

Robbery – Street [a]	15.009***	(1.147)	15.040***	(1.148)
Shooting [a]	9.510***	(1.400)	9.524***	(1.405)
Presence of a Gun	0.440***	(0.019)	0.441***	(0.019)
February [b]	1.123*	(0.060)	1.124*	(0.060)
March [b]	1.060	(0.063)	1.060	(0.063)
April [b]	0.894*	(0.049)	0.894*	(0.049)
May [b]	0.770***	(0.040)	0.770***	(0.040)
June [b]	0.820***	(0.043)	0.820***	(0.043)
July [b]	0.894**	(0.051)	0.894*	(0.051)
August [b]	0.782***	(0.046)	0.782***	(0.046)
September [b]	0.825***	(0.044)	0.825***	(0.044)
October [b]	0.775***	(0.043)	0.775***	(0.043)
November [b]	0.748***	(0.042)	0.748***	(0.042)
December [b]	0.816***	(0.048)	0.816***	(0.048)
District 2[c]	1.008	(0.075)	1.008	(0.075)
District 3[c]	1.157	(0.094)	1.157	(0.094)
District 4[c]	1.154	(0.095)	1.154	(0.095)
District 5[c]	1.078	(0.079)	1.078	(0.079)
District 6[c]	0.965	(0.078)	0.965	(0.079)
District 7[c]	1.079	(0.093)	1.079	(0.093)
District 8[c]	1.125	(0.089)	1.124	(0.089)
District 9[c]	1.074	(0.084)	1.074	(0.084)
Level 2 Variance	0.053	(0.009)	0.053	(0.009)
Constant	0.013***	(0.002)	0.013***	(0.002)
Observations	112,314	112,314	112,314	112,314
Number of groups	643	643	643	643

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05
[a] Larceny from Auto is reference group
[b] January is reference group
[c] District 1 is reference group
SE=Robust standard errors clustered at the census tract

Table 5. Regression of Crime and Neighborhood Characteristics on Probability of Arrest with Dynamic Measures of Threat

	Model 3		Model 4	
	B (Odds Ratio)	*SE*	*B (Odds Ratio)*	*SE*
Total Population	1.000	(3.31e-05)	1.000	(3.31e-05)
Number of Calls	1.000	(1.74e-04)	1.000	(1.74e-04)
Proportion Black	0.785**	(0.064)	0.788**	(0.071)
Officer-initiated	1.284*	(0.137)	1.286*	(0.143)
Officer-initiated x Proportion Black	0.923	(0.118)	0.920	(0.124)
Disadvantage Index	1.025	(0.034)	1.027	(0.035)
Change in Proportion Black	1.185	(0.160)	…	…
Officer-initiated x Change in Proportion Black	0.952	(0.268)	…	…
Negative % Change Proportion Black	…	…	0.974	(0.049)
Positive % Change Proportion Black	…	…	1.037	(0.052)
Proportion Males 15-24	1.600	(0.604)	1.573	(0.600)
Proportion with a Mortgage	1.027	(0.080)	1.029	(0.081)
Proportion Latino	1.010	(0.273)	1.089	(0.272)
Proportion Limited English	0.509	(0.214)	0.507	(0.210)
Proportion Vacant	1.236	(0.182)	1.235	(0.182)
Proportion Renter Occupied	1.269**	(0.113)	1.270**	(0.112)
Aggravated assault [a]	29.138***	(2.138)	29.141***	(2.139)
Arson [a]	5.849**	(1.027)	5.845***	(1.028)
Auto theft [a]	2.799***	(0.242)	2.799***	(0.242)
Burglary [a]	3.411***	(0.260)	3.412***	(0.260)
Homicide [a]	58.966***	(6.497)	58.983***	(6.496)
Larceny [a]	3.216***	(0.312)	3.216***	(0.312)

Rape [a]	19.212***	(2.419)	19.209***	(2.415)
Robbery – Carjacking [a]	22.403***	(2.523)	22.396***	(2.521)
Robbery – Commercial [a]	22.908***	(1.936)	22.913***	(1.935)
Robbery – Residential [a]	56.963***	(5.541)	56.971***	(5.541)
Robbery – Street [a]	15.052***	(1.151)	15.053***	(1.151)
Shooting [a]	9.532***	(1.406)	9.532***	(1.406)
Presence of a Gun	0.441***	(0.019)	0.441***	(0.019)
February [b]	1.124*	(0.060)	1.123*	(0.060)
March [b]	1.060	(0.063)	1.060	(0.063)
April [b]	0.894*	(0.049)	0.894*	(0.049)
May [b]	0.769***	(0.040)	0.769***	(0.040)
June [b]	0.820***	(0.043)	0.820***	(0.043)
July [b]	0.894**	(0.051)	0.894*	(0.051)
August [b]	0.781***	(0.046)	0.782***	(0.046)
September [b]	0.825***	(0.044)	0.825***	(0.044)
October [b]	0.775***	(0.043)	0.774***	(0.043)
November [b]	0.748***	(0.042)	0.748***	(0.042)
December [b]	0.816***	(0.048)	0.816***	(0.048)
District 2[c]	1.009	(0.074)	1.010	(0.075)
District 3[c]	1.149	(0.092)	1.146	(0.091)
District 4[c]	1.129	(0.093)	1.137	(0.095)
District 5[c]	1.071	(0.078)	1.073	(0.079)
District 6[c]	0.960	(0.078)	0.961	(0.078)
District 7[c]	1.076	(0.092)	1.077	(0.092)
District 8[c]	1.114	(0.087)	1.114	(0.089)
District 9[c]	1.054	(0.084)	1.052	(0.083)
Level 2 Variance	0.052	(0.009)	0.052	(0.009)
Constant	0.013***	(0.002)	0.013***	(0.002)

Observations	112,314	112,314	112,314	112,314
Number of groups	643	643	643	643

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05

[a] Larceny from Auto is reference group

[b] January is reference group

[c] District 1 is reference group

SE=Robust standard errors clustered at the census tract

Table 6. Regression of Crime and Neighborhood Characteristics on Probability of Arrest with Victim Characteristics and Dynamic Measures of Threat

	Model 5		Model 6	
	B (Odds Ratio)	*SE*	*B (Odds Ratio)*	*SE*
Total Population	1.000**	(2.61e-05)	1.000**	(2.64e-05)
Number of Calls	1.000	(3.92e-05)	1.000	(3.86e-05)
Proportion Black	0.718***	(0.064)	0.717***	(0.063)
Officer-initiated	1.133	(0.152)	1.123	(0.138)
Officer-initiated x Proportion Black	1.023	(0.164)	1.029	(0.153)
Change in Proportion Black	…	…	1.216	(0.159)
Officer-initiated x Change in Proportion Black	…	…	0.773	(0.250)
Disadvantage	1.019	(0.031)	1.011	(0.031)
Proportion Males 15-24	1.202	(0.357)	1.245	(0.377)
Proportion with a Mortgage	1.081	(0.070)	1.066	(0.069)
Proportion Latino	0.987	(0.195)	1.012	(0.205)
Proportion Limited English	0.729	(0.286)	0.723	(0.290)
Proportion Vacant	1.309	(0.180)	1.310*	(0.179)
Proportion Renter Occupied	1.227*	(0.105)	1.243*	(0.110)
Female Victim	1.375***	(0.041)	1.375***	(0.041)
White Victim	0.924	(0.038)	0.920*	(0.038)
Aggravated assault [a]	30.499***	(2.555)	30.470***	(2.557)
Arson [a]	6.082***	(1.275)	6.106***	(1.279)
Auto theft [a]	2.761***	(0.285)	2.759***	(0.285)

Burglary [a]	2.839***	(0.261)	2.837***	(0.261)
Homicide [a]	65.979***	(7.835)	65.106***	(7.825)
Larceny [a]	1.384***	(0.136)	1.384***	(0.136)
Rape [a]	17.270***	(2.316)	17.275***	(2.322)
Robbery – Carjacking [a]	23.965***	(2.996)	23.985***	(3.003)
Robbery – Commercial [a]	20.176***	(4.987)	20.187***	(4.992)
Robbery – Residential [a]	53.743***	(5.543)	53.724***	(5.552)
Robbery – Street [a]	16.401***	(1.411)	16.425***	(1.416)
Shooting [a]	10.667***	(1.714)	10.666***	(1.713)
Presence of a Gun	0.448***	(0.022)	0.447***	(0.022)
February [b]	1.100	(0.076)	1.099	(0.076)
March [b]	1.033	(0.077)	1.033	(0.077)
April [b]	0.868*	(0.062)	0.867*	(0.062)
May [b]	0.722***	(0.047)	0.722***	(0.047)
June [b]	0.753***	(0.054)	0.753***	(0.054)
July [b]	0.830***	(0.056)	0.829***	(0.056)
August [b]	0.704**	(0.050)	0.703***	(0.050)
September [b]	0.776***	(0.050)	0.775***	(0.050)
October [b]	0.714***	(0.046)	0.714***	(0.046)
November [b]	0.662***	(0.046)	0.661***	(0.046)
December [b]	0.785***	(0.056)	0.785***	(0.056)
District 2[c]	1.039	(0.073)	1.038	(0.072)
District 3[c]	1.164	(0.092)	1.155	(0.090)
District 4[c]	1.107	(0.091)	1.083	(0.090)
District 5[c]	1.028	(0.071)	1.021	(0.071)
District 6[c]	0.974	(0.081)	0.967	(0.080)
District 7[c]	1.048	(0.077)	1.042	(0.076)
District 8[c]	1.070	(0.083)	1.059	(0.082)

District 9[c]	1.074	(0.079)	1.051	(0.078)
Level 2 Variance	0.006	(0.008)	0.005	(0.007)
Constant	0.013***	(0.002)	0.013***	(0.002)
Observations	76,521	76,521	76,521	76,521
Number of groups	643	643	643	643

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

[a] Larceny from Auto is reference group
[b] January is reference group
[c] District 1 is reference group
SE=Robust standard errors clustered at the census tract

Figure 1. Predictive Probability of Arrest by Block Group Proportion Black with 95% CIs

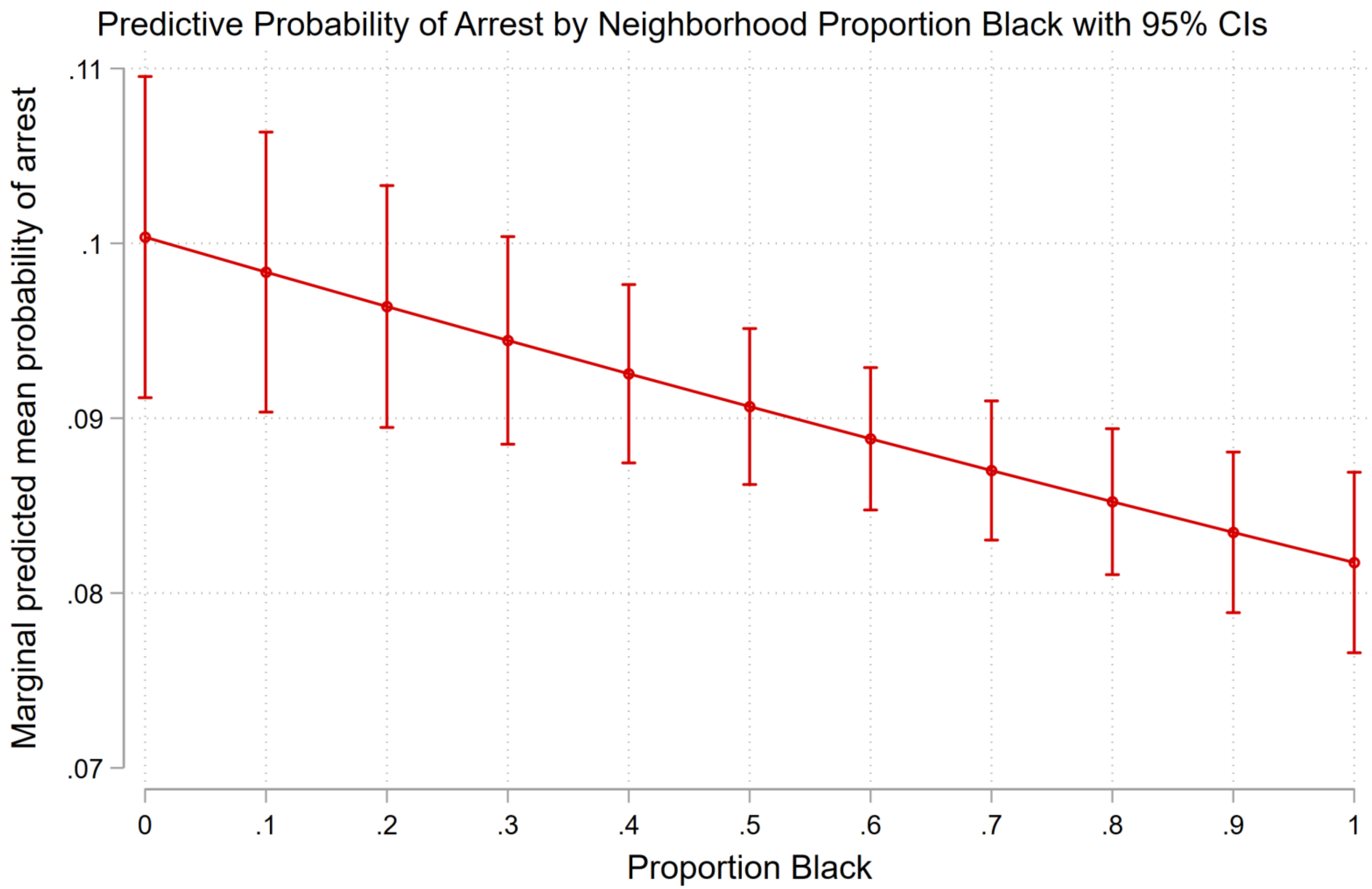


Figure 2. Predictive Probability of Arrest by Block Group Proportion Black with 95% CIs, Officer-Initiated vs. Citizen-Initiated

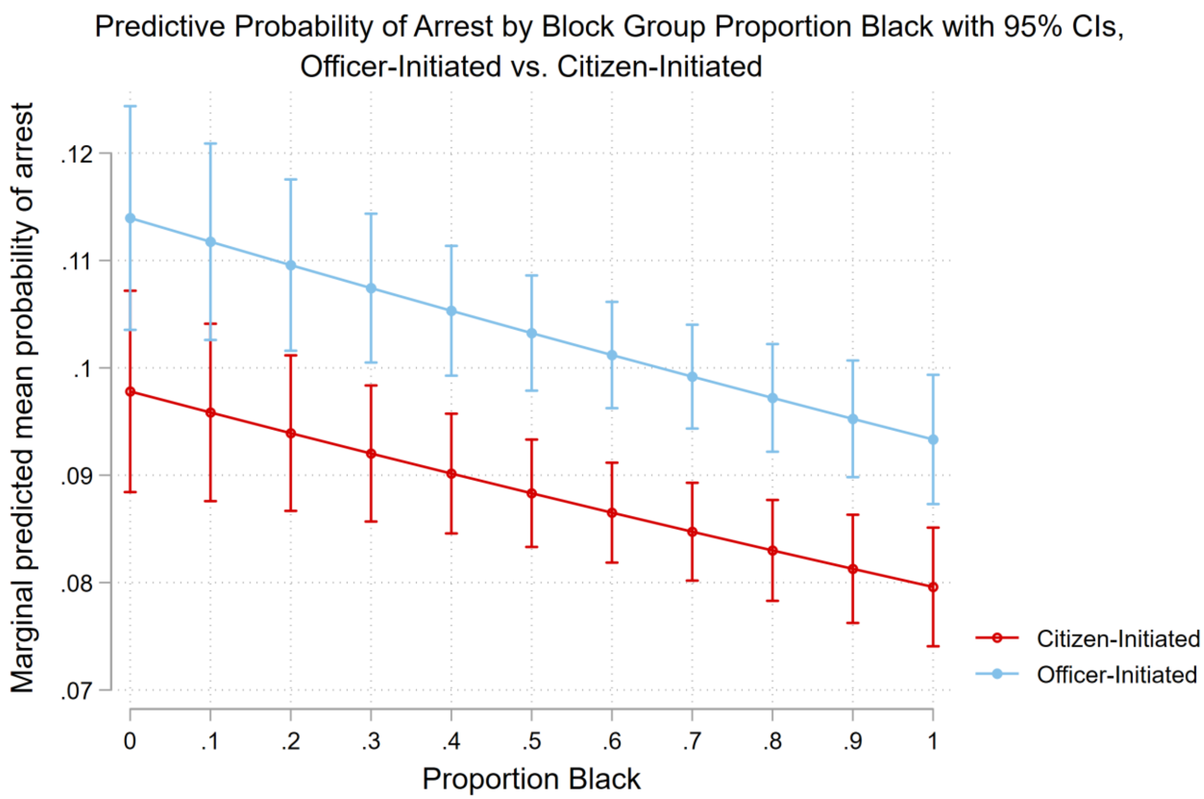


Figure 3. Predictive Probability of Arrest by Block Group Proportion Black with 95% CIs, Officer-Initiated vs. Citizen-Initiated (Varying slopes)

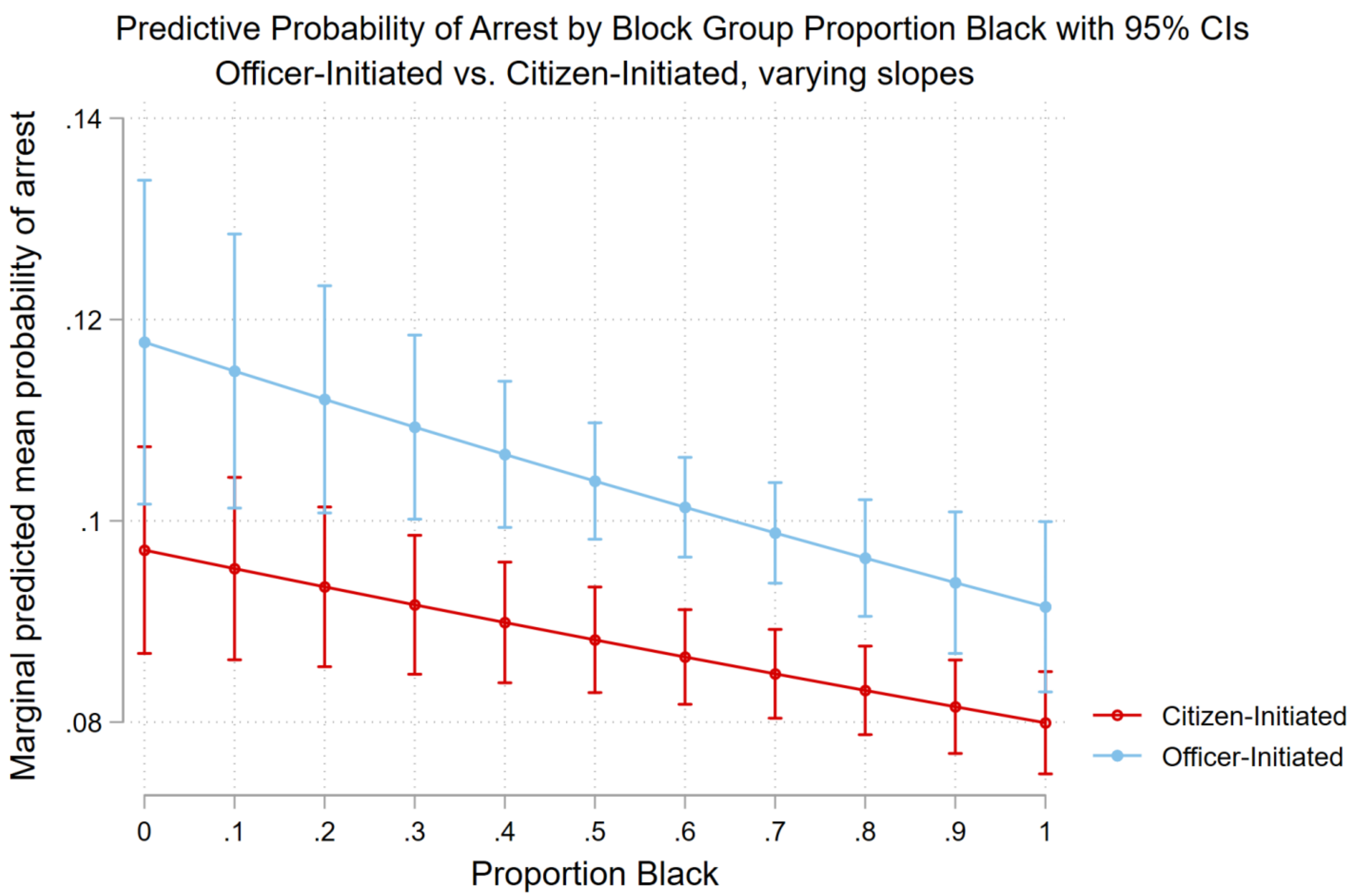


Figure 4. Predictive Probability of Arrest by Block Group Proportion Black with 95% CIs, by Victim Gender

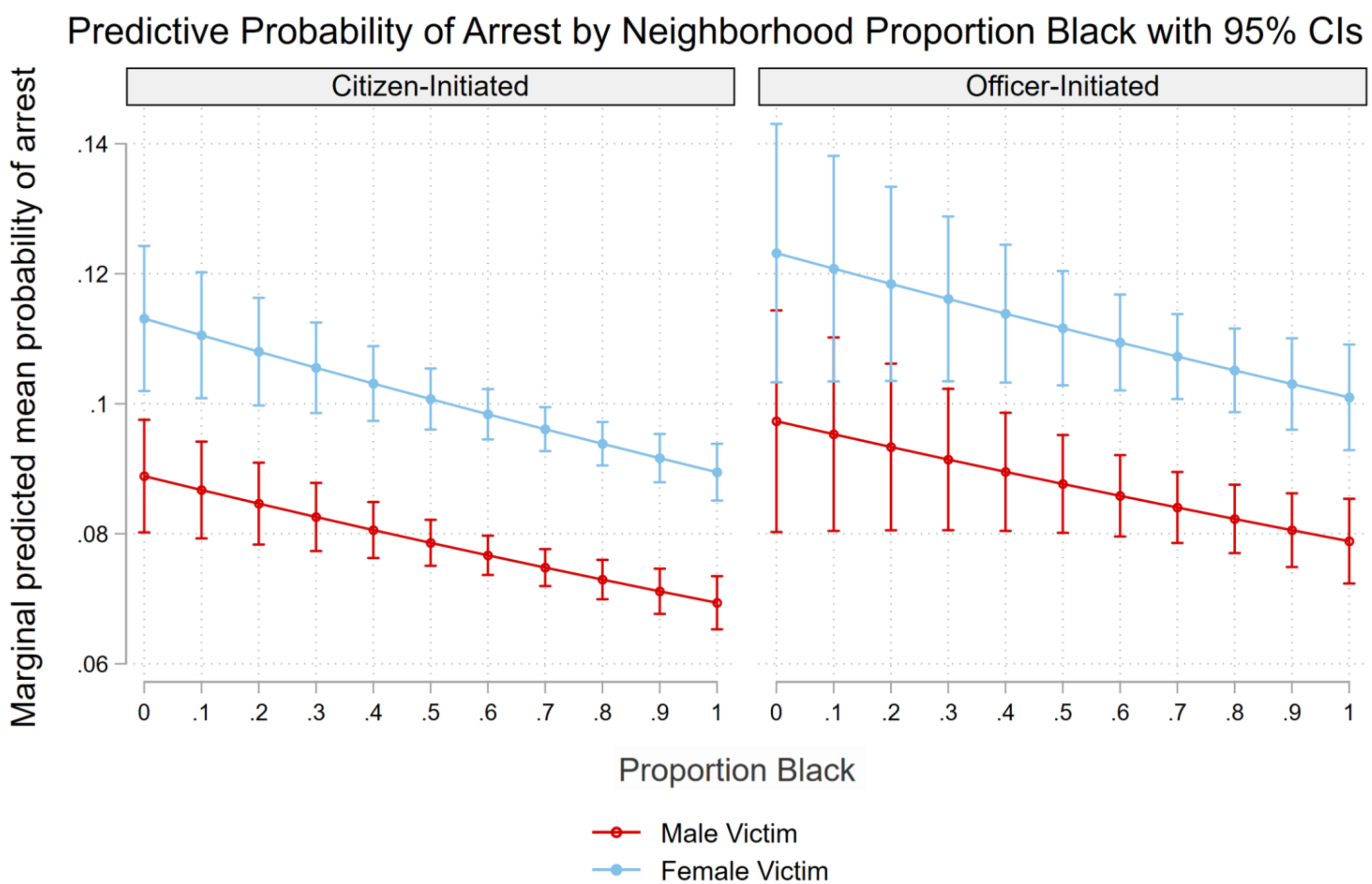


Figure 5. Predictive Probability of Arrest by Block Group Proportion Black with 95% CIs, by Victim Race

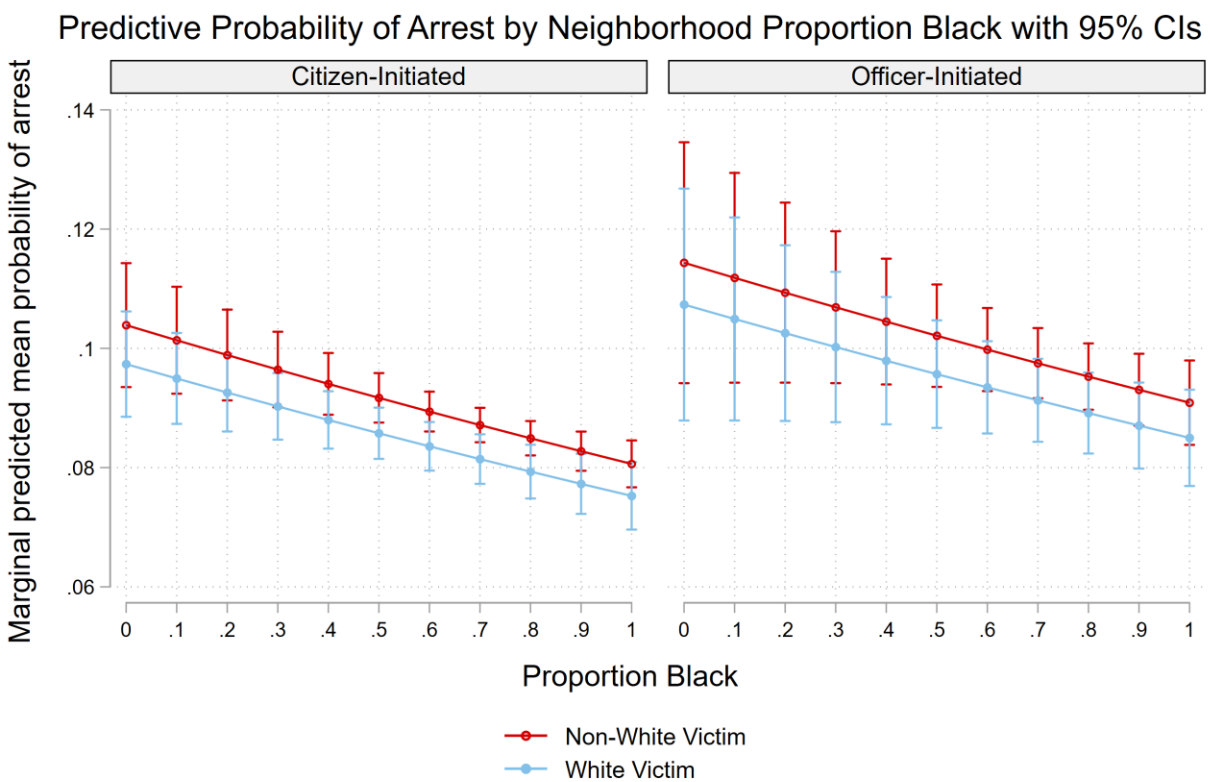


Figure 6. Predictive Probability of Arrest by Block Group Quartile Proportion Black with 95% CIs

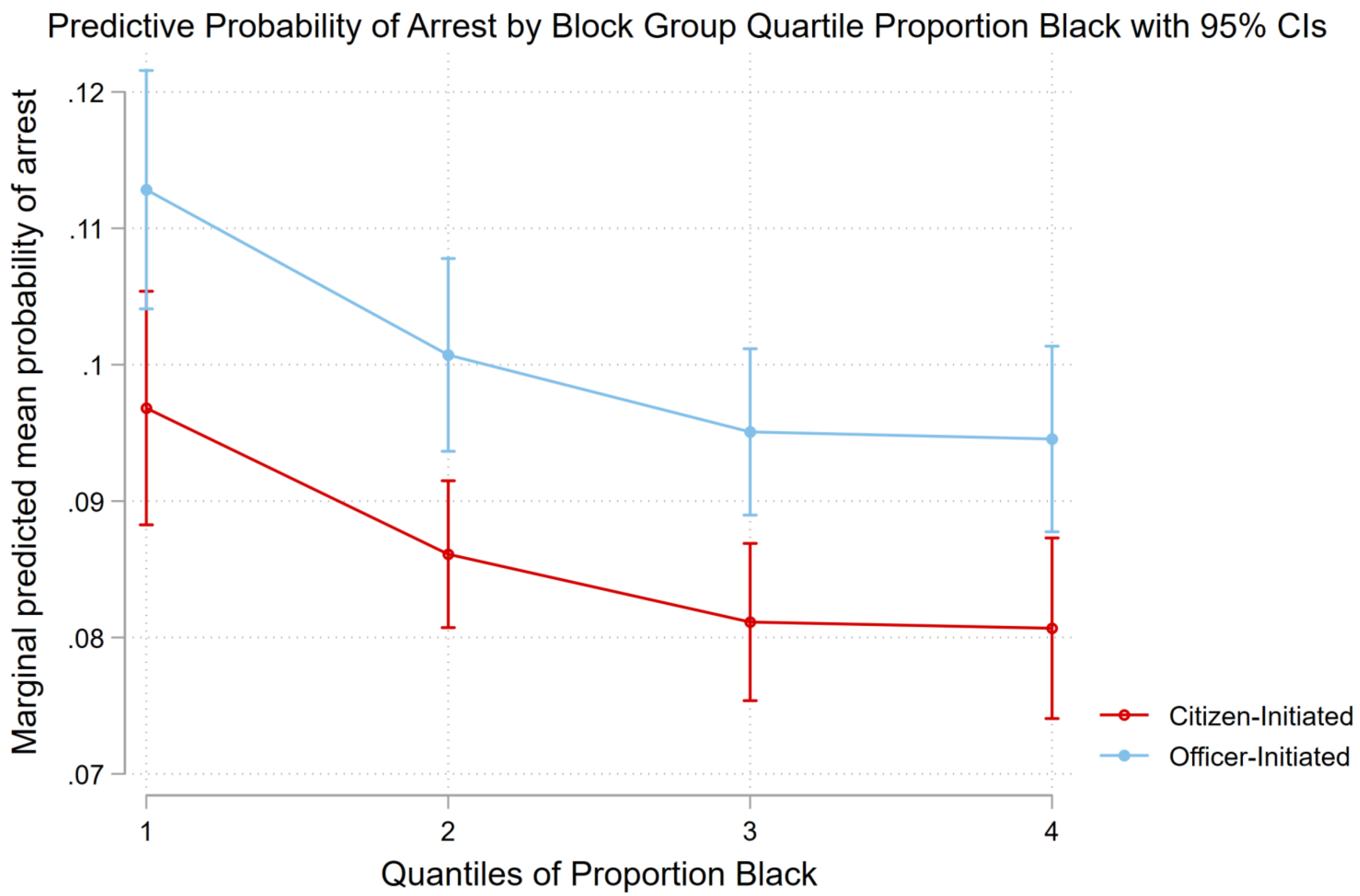
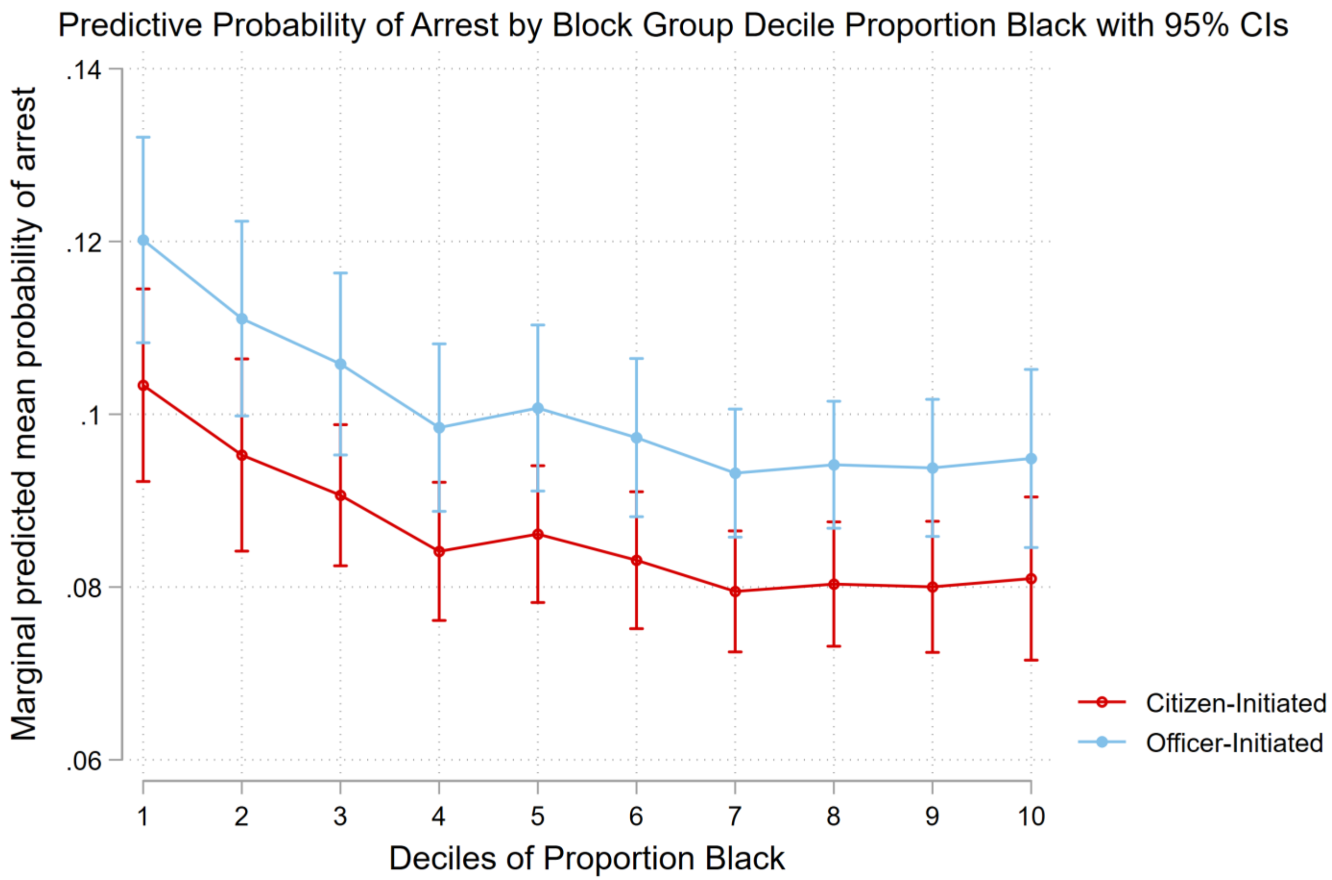


Figure 7. Predictive Probability of Arrest by Block Group Decile Proportion Black with 95% CIs



Appendix A. Summary of Racial Threat Tests with Arrest as the Outcome

Article	Context	Citizen- or officer-initiated	Measure of Threat	Static or change measure of threat?	Unit of Analysis	Multi-level?	Outcome	Main Findings
Andersen, 2015	Nation-wide	Does not distinguis h; data is self-reported	racial/ethnic composition (% Black and % Hispanic) and racial/ethnic inequality (ratio of Black to White unemployment and ratio of Hispanic to White unemployment)	Static	Individual and county-level; nationally representative	Yes	Youth arrest	Support for benign neglect: The magnitude of the effect of individual race on arrest risk depends on the racial composition of the county, where the racial disparities in arrest rates are lower in places with a larger percent Black
Eitle and Monahan, 2009	Nation-wide	UCR data, so all arrests	racial/ethnic composition (Dummy for >40% Black; disadvantage index; racial inequality index; political power (presence of Black mayor)	Static	260 cities	No	Race-specific drug arrest rates	Partial support for racial threat: only race-based economic competition was a significant predictor of drug arrest rates, and was associated with both White and Black drug arrest rates

Eitle et al., 2002	Predominantly White counties	NIBRS, all violent felony arrests	Political threat (ratio of Black-to-white voting); economic threat (ratio of white-to-Black unemployment); Black-on-White crime	Static	Counties in South Carolina	No	Black-to-white arrest ratio, violent felony arrests	Support for the Black crime hypothesis of racial threat but not for political or economic threat: Black-on-White crime has a substantive positive effect on Black arrest levels, but there is no effect of Black-on-Black crime
Gaston, 2019	St. Louis is evenly Black-White split	Officers self-reported accounts of a representative sample of official drug arrests (could be either officer- or citizen-initiated)	racial/ethnic composition (% Black)	Static	Individual arrests in St. Louis neighborhoods	Yes	Arrests, drugs	support for racial threat: conducted stops at higher rates in Black neighborhoods

Huff, 2021	Phoenix is mostly split White-Hispanic	CAD data about all police-civilian contacts and arrests, controls for civilian-versus officer-initiated contact	disadvantage factor variable, % Hispanic and % Black (although does not specifically mention RTT)	Static	Incident level and census tracts in Phoenix	Yes	Arrest probability	Support for racial/ethnic threat: arrest was more likely in Hispanic and Black neighborhoods, after controlling for situational and officer-level characteristics
Kane et al., 2013	Majority Black	All misdemeanor arrests, not distinguished by initiation	racial/ethnic composition change (% Black change and % Latino change between 1990 and 2000; level change between 1990 and 2000 per tract; difference score multiplied by 1990 White population in 1990)	Change	Census Tracts in DC	No	Misdemeanor arrests (count per tract)	Support for racial threat: Change in Black population or Latino population was not associated with arrests except for in majority White communities, effect of change in Black population mediated by baseline white residential representation,

Kirk and Matsuda, 2011	Majority White, substantial Black population	Official arrest data for sampled individuals, not distinguished by initiation	racial/ethnic composition (% Black and % Latino); concentrated disadvantage	Static	individuals and families within neighborhood clusters in Chicago	Yes	probability of arrest	Support for benign neglect (although framed as legal cynicism): individuals are less likely to be arrested following the commission of a crime in predominantly Black neighborhoods
Kirk, 2008	Majority White, substantial Black population	Official arrest data for sampled individuals, not distinguished by initiation	racial/ethnic composition (% Black and % Latino); concentrated poverty	Static	Individuals, families, and neighborhoods within Chicago	Yes	Arrests	No support for racial threat: racial composition is not associated with racial disparities in arrests, but concentrated poverty explains a large portion of black-white differences in arrest
Levchak, 2017	Nation-wide	Officer-initiated stops	racial/ethnic composition (% Black, % Latino, % Asian, % Other)	Static	Individuals and precincts	Yes	Police stop outcomes, including arrest	Partial support for racial threat: % Black is positively associated with the odds of being frisked, but no association with probability of arrest

Liska and Chamlin, 1984	Nation-wide	All arrests, does not distinguish by initiation	racial/ethnic composition (% nonwhite), segregation (dissimilarity index), and economic inequality (Gini coefficient)	Static	76 Cities	No	Property and personal arrest rates	Support for racial threat and benign neglect: percent nonwhite is associated with higher total arrest rates, but percent nonwhite is negatively associated with arrest rates for nonwhites
Lum, 2011	Majority White	police calls for service, initiated by either a police officer or citizen	racial/ethnic composition, concentrated disadvantage	Static	Census block groups within a city	No	Police pathway decisions, including arrest	Support for benign neglect: a greater proportion of Black residents is associated with officers' decisions to downgrade crime classifications
Ousey and Lee, 2008	Nation-wide	All arrests	White-Black exposure index, dissimilarity index, and White/Black unemployment ratio	Static	136 US cities	No	Black-White disparity in arrest rates	No support for either racial threat or benign neglect
Parker et al., 2005	Nation-wide	All arrests	Black composition, racial inequality, and growth in Black immigrant population	Change and static	Cities with >100,000 residents	No	Black arrest rates	Support for benign neglect hypothesis

Stolzenberg, D'Alessio, and Eitle, 2004	Nation-wide	All crimes reported to NIBRS where the victim could identify the race of the offender	racial/ethnic composition (% Black); Black -to-White unemployment ratio; racial segregation (White-Black dissimilarity index)	Static	Individuals and 182 cities	Yes	Black probability of arrest, violent crimes	No support for racial threat: Black citizens had a lower probability of arrest in cities with relatively large Black populations; in cities with more racial segregation, Black people have a reduced risk of being arrested relative to Whites
Stucky, 2012	Nation-wide	All arrests	racial/ethnic composition (% Black and % Black squared) and Black disadvantage	Static	100 US cities	No	Black arrest rates, violent crime	No support for racial threat: Black violent crime arrest rates were curvilinearly negatively associated with larger percentages of Black residents, but this relationship depends on characteristics of the city's political system

Appendix B. Additional Descriptive Tables

Table 1. City-wide Crime Reports by Part 1 Crime Types*

	Citizen-initiated call		Officer-initiated calls		All calls	
Part 1 Crime Calls	*n*	%	*n*	%	*n*	%
Aggravated assault	10,669	11.12	1,645	8.37	12,314	10.96
Arson	63	.07	558	2.84	621	0.55
Auto theft	10,267	11.08	2,685	13.65	12,952	11.53
Burglary	20,067	21.66	1,430	7.27	21,497	19.14
Homicide	792	0.85	156	0.79	948	0.84
Larceny	22,528	24.32	6,676	33.95	29,204	26.00
Larceny from Auto	13,187	14.23	4,039	20.54	17,226	15.34
Rape	738	0.80	234	1.19	972	0.87
Robbery - Carjacking	1,038	1.12	234	1.19	1,272	1.13
Robbery - Commercial	2,433	2.63	169	0.86	2,602	2.32
Robbery - Residential	1,267	1.37	107	0.54	1,373	1.22
Robbery- Street	8,345	9.01	1,483	7.54	9,828	8.75
Shooting	1,256	1.36	249	1.27	1,505	1.34
All Part 1 crimes	92,649	82.49	19,665	17.51	112,314	100

*City-Wide refers to the 643 block groups that are included in the study

Table 2. Block Group Counts of Part 1 Crime Reports by Crime Type

	Citizen-initiated call			Officer-initiated Calls			All calls		
Part 1 Crime Calls	*Mean*	*SD*	*Range*	*Mean*	*SD*	*Range*	*Mean*	*SD*	*Range*
Aggravated assault	16.596	16.086	(0, 199)	2.560	4.172	(0, 66)	19.156	19.379	(0, 265)
Arson	0.098	0.327	(0, 2)	0.868	1.299	(0, 8)	0.966	1.395	(0, 8)
Auto theft	15.978	10.130	(0, 94)	4.176	3.784	(0, 31)	20.154	12.596	(0, 112)
Burglary	31.227	20.800	(0, 166)	2.224	2.970	(0, 23)	33.451	22.343	(0, 176)
Homicide	1.235	1.588	(0, 9)	0.250	0.762	(0, 12)	1.485	1.913	(0, 16)
Larceny	35.070	52.932	(1, 907)	11.187	16.474	(0, 306)	46.257	68.074	(2, 1213)
Larceny from Auto	20.529	23.851	(1, 417)	6.978	9.260	(0, 132)	27.507	32.234	(1, 549)
Rape	1.149	2.122	(0, 36)	0.364	0.746	(0, 7)	1.513	2.527	(0, 43)
Robbery - Carjacking	1.616	1.932	(0, 17)	36.39	0.673	(0, 5)	1.980	2.193	(0, 18)
Robbery - Commercial	3.784	7.126	(0, 89)	0.263	0.704	(0, 7)	4.047	7.563	(0, 95)
Robbery - Residential	1.970	2.171	(0, 14)	0.166	0.455	(0, 3)	2.137	2.333	(0, 15)
Robbery- Street	12.980	15.795	(0, 200)	2.306	4.671	(0, 69)	15.286	19.713	(0, 269)
Shooting	1.964	2.703	(0, 18)	0.401	0.895	(0, 10)	2.365	3.241	(0, 25)
All Part 1 crimes	144.196	127.57	(10, 2043)	32.107	36.606	(1, 659)	176.303	161.6991	(13, 2702)

N=643

Table 3. Block Group Proportion of Crime Types of Part 1 Crime Reports

	Citizen-initiated call			Officer-initiated Calls			All calls		
Part 1 Crime Calls	*Mean*	*SD*	*Range*	*Mean*	*SD*	*Range*	*Mean*	*SD*	*Range*
Aggravated assault	11.34%	6.269	(0, 30.77)	7.39%	6.926	(0, 36.36)	10.69%	5.751	(0, 29.41)
Arson	0.07%	0.265	(0, 2.43)	3.11%	4.716	(0, 33.33)	0.60%	0.859	(0, 5)
Auto theft	12.42%	5.611	(0, 36.36)	15.59%	12.260	(0, 100)	12.88%	5.692	(0, 37.74)
Burglary	23.53%	9.096	(0, 66.67)	7.07%	7.737	(0, 61.53)	20.66%	8.047	(0, 56.63)
Homicide	0.93%	1.265	(0, 7.04)	0.78%	2.167	(0, 18.75)	0.91%	1.170	(0, 6.25)
Larceny	21.95%	9.867	(5.13, 84.16)	32.48%	14.230	(0, 82.61)	23.85%	9.598	(5.88, 83.94)
Larceny from Auto	14.67%	7.894	(1.15, 58.97)	22.47%	16.255	(0, 100)	16.06%	8.858	(2.25, 62.75)
Rape	.78%	1.027	(0, 7.41)	1.10%	2.250	(0, 15.79)	0.84%	0.982	(0, 7.14)
Robbery - Carjacking	1.18%	1.276	(0, 7.84)	1.33%	2.881	(0, 0.2)	1.19%	1.173	(0, 7.14)
Robbery - Commercial	2.04%	2.953	(0, 27.78)	0.69%	1.894	(0, 18.18)	1.80%	2.519	(0, 20.27)
Robbery - Residential	1.45%	1.461	(0, 10.45)	0.52%	1.600	(0, .125)	1.29%	1.259	(0, 7.79)
Robbery - Street	8.24%	4.618	(0, 28.13)	6.20%	6.411	(0, 43.75)	7.86%	4.211	(0, 25)
Shooting	1.40%	1.751	(0, 10.14)	1.27%	2.782	(0, 23.08)	1.38%	1.658	(0, 10)
N=643									

Table 4. City-wide Arrests by Part 1 Crime Type

	Citizen-initiated calls			Officer-initiated calls			All calls		
Crime Type	*N*	*n*	%	*N*	*n*	%	*N*	*n*	%
All Crimes	92,649	8,102	8.74	19,665	1,721	8.75	112,314	9,823	8.75
Aggravated assault	10,669	2,981	27.94	1,645	420	25.53	12,314	3,401	27.62
Arson	63	6	9.52	558	49	8.78	621	55	8.86
Auto theft	10,267	365	3.56	2,685	139	5.18	12,952	504	3.89
Burglary	20,067	864	4.31	1,430	118	8.25	21,497	982	4.57
Homicide	792	220	27.78	156	54	34.62	948	274	28.90
Larceny	22,528	1,062	4.71	6,676	363	5.44	29,204	1,425	4.88
Larceny from Auto	13,187	193	1.46	4,039	62	1.54	17,226	255	1.48
Rape	738	167	22.63	234	50	21.37	972	217	22.33
Robbery - Carjacking	1,038	157	15.13	234	48	20.51	1,272	205	16.12
Robbery - Commercial	2,433	441	18.13	169	56	33.14	2,602	497	19.10
Robbery - Residential	1,266	506	39.97	107	44	41.12	1,373	550	40.06
Robbery - Street	8,345	1,079	12.93	1,483	294	19.82	9,828	1,373	13.97
Shooting	1,256	61	4.86	249	24	9.64	1,505	85	5.65

Table 5. Block Group Arrest by Part 1 Crime Type

	Citizen-initiated call			Officer-initiated Calls			All calls		
Arrests for Part 1 Crimes	*Mean*	*SD*	*Range*	*Mean*	*SD*	*Range*	*Mean*	*SD*	*Range*
Aggravated assault	4.636	4.726	(0, 50)	0.653	1.565	(0, 26)	5.289	5.736	(0, 76)
Arson	0.009	0.096	(0, 1)	0.076	0.288	(0, 2)	0.086	0.301	(0, 2)
Auto theft	0.568	0.8859	(0, 8)	0.216	0.540	(0, 4)	0.784	1.099	(0, 9)
Burglary	1.344	1.718	(0, 14)	0.184	0.500	(0, 5)	1.527	1.913	(0, 15)
Homicide	0.342	0.654	(0, 4)	0.084	0.373	(0, 6)	0.426	0.781	(0, 8)
Larceny	1.652	5.221	(0, 58)	0.565	1.841	(0, 24)	2.216	6.706	(0, 82)
Larceny from Auto	0.300	0.739	(0, 11)	0.096	0.391	(0, 5)	0.397	0.945	(0, 16)
Rape	0.260	0.577	(0, 4)	0.078	0.296	(0, 3)	0.337	0.658	(0, 4)
Robbery - Carjacking	0.244	0.528	(0, 3)	0.075	0.280	(0, 2)	0.319	0.614	(0, 3)
Robbery - Commercial	0.686	1.791	(0, 21)	0.087	0.342	(0, 3)	0.773	1.987	(0, 24)
Robbery - Residential	0.787	1.153	(0, 8)	0.068	0.265	(0, 2)	0.855	1.225	(0, 9)
Robbery- Street	1.678	2.682	(0, 35)	0.457	1.391	(0, 22)	2.135	3.806	(0, 54)
Shooting	0.095	0.328	(0, 2)	0.037	0.213	(0, 3)	0.132	0.402	(0, 3)
All Part 1 crimes	12.600	13.726	(0, 179)	2.677	5.301	(0, 96)	15.277	18.293	(0, 275)

N=643

Table 6. Block Group Percentage of Calls that Resulted in Arrest by Part 1 Crime Type

	Citizen-initiated call			Officer-initiated Calls			All calls		
Part 1 Crime Calls	*Mean*	*SD*	*Range*	*Mean*	*SD*	*Range*	*Mean*	*SD*	*Range*
Aggravated assault	27.24%	17.787	(0, 100)	17.24%	28.867	(0, 100)	26.77%	16.298	(0, 100)
Arson	0.933%	9.622	(0, 100)	4.56%	18.459	(0, 100)	4.97%	19.019	(0, 100)
Auto theft	3.50%	5.576	(0, 50)	4.52%	13.354	(0, 100)	3.82%	5.386	(0, 40)
Burglary	4.16%	5.386	(0, 66.67)	5.46%	16.601	(0, 100)	4.36%	5.556	(0, 66.67)
Homicide	16.94%	32.119	(0, 100)	5.72%	21.984	(0, 100)	18.97%	32.920	(0, 100)
Larceny	2.79%	4.482	(0, 28.08)	3.34%	7.345	(0, 50)	2.91%	4.172	(0, 27.01)
Larceny from Auto	1.22%	2.809	(0, 20)	1.23%	6.339	(0, 100)	1.21%	2.469	(0, 16.67)
Rape	13.83%	30.494	(0, 100)	6.02%	22.773	(0, 100)	15.63%	30.804	(0, 100)
Robbery - Carjacking	10.64%	25.233	(0, 100)	5.82%	22.295	(0, 100)	12.92%	26.921	(0, 100)
Robbery - Commercial	10.11%	21.445	(0, 100)	5.16%	20.046	(0, 100)	10.74%	21.839	(0, 100)
Robbery - Residential	27.59%	35.996	(0, 100)	5.78%	22.631	(0, 100)	28.08%	35.894	(0, 100)
Robbery - Street	12.33%	14.65	(0, 100)	12.48%	24.927	(0, 100)	12.86%	13.282	(0, 100)
Shooting	3.12%	13.133	(0, 100)	2.67%	15.219	(0, 100)	3.96%	14.915	(0, 100)
All Part 1 crimes	8.19%	3.698	(0, 25)	7.08%	6.551	(0, 44.44)	8.00%	3.536	(0, 24.92)

N=643

Table 7. City-Wide Call-Level Variables

	Citizen-initiated call			Officer-initiated calls			All calls		
Variables	*N*	*n*	%	*N*	*n*	%	*N*	*n*	%
Gun present	92,649	9,668	10.44	19,665	1,480	7.53	112,314	11,148	9.93
Female victim	69,722	33,646	48.26	15,346	7,304	47.60	85,068	44,950	48.14
White victim	63,154	19,779	31.32	13,731	5,075	36.96	76,885	24,854	32.33

Table 8. Block-Group Call-Level Variable Counts

	Citizen-initiated call			Officer-initiated Calls			All calls		
Call-Level Characteristics	*Mean*	*SD*	*Range*	*Mean*	*SD*	*Range*	*Mean*	*SD*	*Range*
Gun present	15.036	12.466	(0, 129)	2.302	2.970	(0, 36)	17.375	14.695	(0, 162)
Female victim	52.327	39.002	(3, 582)	11.359	12.241	(0, 217)	63.686	49.828	(4, 799)
White victim	30.761	39.735	(0, 505)	7.893	12.294	(0, 195)	38.653	51.155	(0, 700)

Table 9. Block-Group Call-Level Variable Percentages

	Citizen-initiated call			Officer-initiated Calls			All calls		
Call-Level Characteristics	*Mean*	*SD*	*Range*	*Mean*	*SD*	*Range*	*Mean*	*SD*	*Range*
Gun present	10.33%	4.639	(0, 26.56)	7.58%	7.195	(0, 46.67)	9.84%	4.421	(0, 23.15)
Female victim	48.79%	7.856	(22.22, 80.95)	48.93%	14.347	(0, 100)	48.77%	7.272	(27.27, 73.21)
White victim	31.75%	29.901	(0, 100)	33.82%	29.871	(0, 100)	32.13%	29.497	(0, 100)

Table 10. Block-Group Neighborhood Characteristics

Variables	N	mean	Sd	min	max
Total Population	643	958.8	500.3	95	3,828
Proportion Males 15-24	643	0.064	0.051	0	0.423
Proportion in Poverty	643	0.246	0.172	0	0.867
Proportion with a Mortgage	643	0.649	0.228	0	1
Proportion speaking limited English	643	0.020	0.047	0	0.383
Proportion Vacant	643	0.194	0.148	0	0.663
Proportion Renter occupied	643	0.508	0.250	0	1
Unemployment Rate	643	0.148	0.115	0	0.742
Proportion no college	643	0.690	0.235	0	1
Proportion Black	643	0.668	0.347	0	1
Proportion White	643	0.262	0.304	0	1
Proportion Latino	643	0.046	0.086	0	0.787
Proportion Non-White	643	0.738	0.304	0	1
White Neighborhood	643	0.146	0.354	0	1
Black Neighborhood	643	0.608	0.489	0	1
Latino Neighborhood	643	0.002	0.039	0	1
Minority Neighborhood	643	0.047	0.211	0	1
Integrated Neighborhood	643	0.198	0.398	0	1
Proportion Female headed with children	643	0.247	0.174	0	1
Disadvantage Index	643	0.004	0.782	-1.745	2.538
Total Population in 2000	643	1,227	1,077	5	6,375
Proportion Black in 2000	643	0.645	0.359	0	1
Proportion White in 2000	643	0.308	0.336	0	1
Proportion Latino in 2000	643	0.018	0.026	0	0.293

Proportion Non-White in 2000	643	0.692	0.336	0	1
White Neighborhood in 2000	643	0.213	0.410	0	1
Black Neighborhood in 2000	643	0.588	0.493	0	1
Change in Proportion Black	643	0.023	0.139	-1	0.519
Change in Proportion White	643	-0.046	0.140	-0.624	1

Appendix C. Nonlinear Forms of the Relationship between Racial Composition and Probability of Arrest

Table 1. Regression of Crime and Neighborhood Characteristics on Probability of Arrest with Nonlinear Measures of Racial Composition

	Model 1		Model 2		Model 3		Model 4	
	B (Odds Ratio)	*SE*	*B (Odds Ratio)*	*SE*	*B (Odds Ratio)*	*SE*	*B (Odds Ratio)*	*SE*
Total Population	1.000	(3.28e-05)	1.000	(3.31e-05)	1.000	(3.30e-05)	1.000	(3.26e-05)
Number of Calls	1.000	(1.90e-04)	1.000	(1.84e-04)	1.000	(1.82e-04)	1.000	(1.77e-04)
Officer-initiated	1.219***	(0.055)	1.219***	(0.055)	1.219***	(0.055)	1.219***	(0.055)
Disadvantage Index	0.936	(0062)	1.033	(0.036)	1.032	(0.034)	1.041	(0.036)
Proportion Black	0.821*	(0.068)	0.587*	(0.158)	…	…	…	…
Proportion Black x Disadvantage Index	1.153	(0.098)	…	…	…	…	…	…
Proportion Black^2	…	…	1.289	(0.308)	…	…	…	…
2nd Quartile of Proportion Black [d]	…	…	…	…	0.863**	(0.048)	…	…
3rd Quartile of Proportion Black [d]	…	…	…	…	0.801***	(0.049)	…	…
4th Quartile of Proportion Black [d]	…	…	…	…	0.796***	(0.056)	…	…
2nd Decile of Proportion Black [e]	…	…	…	…	…	…	0.901	(0.069)
3rd Decile of Proportion Black [e]	…	…	…	…	…	…	0.845*	(0.058)
4th Decile of Proportion Black [e]	…	…	…	…	…	…	0.770***	(0.062)
5th Decile of Proportion Black [e]	…	…	…	…	…	…	0.793**	(0.071)
6th Decile of Proportion Black [e]	…	…	…	…	…	…	0.759***	(0.059)

7th Decile of Proportion Black [e]	…	…	…	…	…	…	0.718***	(0.062)
8th Decile of Proportion Black [e]	…	…	…	…	…	…	0.728***	(0.062)
9th Decile of Proportion Black [e]	…	…	…	…	…	…	0.724***	(0.065)
10th Decile of Proportion Black [e]	…	…	…	…	…	…	0.735**	(0.074)
Proportion Males 15-24	1.540	(0.592)	1.574	(0.598)	1.491	(0.570)	1.596	(0.615)
Proportion with a Mortgage	1.038	(0.081)	1.053	(0.080)	1.046	(0.079)	1.052	(0.079)
Proportion Latino	1.186	(0.291)	1.092	(0.270)	1.078	(0.261)	1.064	(0.254)
Proportion Limited English	0.556	(0.228)	0.555	(0.230)	0.536	(0.223)	0.612	(0.258)
Proportion Vacant	1.231	(0.184)	1.241	(0.184)	1.240	(0.184)	1.240	(0.185)
Proportion Renter Occupied	1.238*	(0.110)	1.267*	(0.117)	1.262*	(0.117)	1.266*	(0.119)
Aggravated assault [a]	29.142***	(2.144)	29.093***	(2.136)	29.088***	(2.136)	29.116***	(2.139)
Arson [a]	5.812***	(1.029)	5.790***	(1.025)	5.790***	(1.025)	5.796***	(1.026)
Auto theft [a]	2.797***	(0.241)	2.791***	(0.241)	2.791***	(0.241)	2.794***	(0.241)
Burglary [a]	3.409***	(0.259)	3.406***	(0.258)	3.404***	(0.258)	3.408***	(0.258)
Homicide [a]	58.884***	(6.476)	58.810***	(6.465)	58.810***	(6.471)	58.819***	(6.484)
Larceny [a]	3.214***	(0.313)	3.210***	(0.312)	3.211***	(0.312)	3.211***	(0.312)
Rape [a]	19.189***	(2.440)	19.144***	(2.429)	19.158***	(2.431)	19.163***	(2.434)
Robbery – Carjacking [a]	22.381***	(2.527)	22.351***	(2.524)	22.341***	(2.521)	22.380***	(2.525)
Robbery – Commercial [a]	22.870***	(1.908)	22.843***	(1.903)	22.842***	(1.905)	22.828***	(1.900)
Robbery – Residential [a]	56.978***	(5.542)	56.872***	(5.528)	56.871***	(5.525)	56.947***	(5.532)
Robbery – Street [a]	15.023***	(1.148)	15.013***	(1.147)	15.017***	(1.148)	15.024***	(1.150)
Shooting [a]	9.514***	(1.402)	9.504***	(1.400)	9.506***	(1.401)	9.512***	(1.401)
Presence of a Gun	0.441***	(0.019)	0.440***	(0.019)	0.441***	(0.019)	0.441***	(0.019)
February [b]	1.123*	(0.060)	1.122*	(0.060)	1.123*	(0.060)	1.122*	(0.060)
March [b]	1.059	(0.063)	1.059	(0.062)	1.060	(0.063)	1.059	(0.062)
April [b]	0.894*	(0.049)	0.893*	(0.049)	0.894*	(0.049)	0.893*	(0.049)

May [b]	0.769***	(0.040)	0.769***	(0.040)	0.770***	(0.040)	0.769***	(0.040)
June [b]	0.820***	(0.043)	0.820***	(0.043)	0.820***	(0.043)	0.820***	(0.043)
July [b]	0.894*	(0.051)	0.894*	(0.051)	0.894*	(0.051)	0.894*	(0.051)
August [b]	0.782***	(0.046)	0.782***	(0.046)	0.782***	(0.046)	0.782***	(0.046)
September [b]	0.825***	(0.044)	0.825***	(0.044)	0.825***	(0.044)	0.825***	(0.044)
October [b]	0.775***	(0.043)	0.774***	(0.043)	0.774***	(0.043)	0.774***	(0.043)
November [b]	0.748***	(0.042)	0.747***	(0.042)	0.748***	(0.042)	0.747***	(0.042)
December [b]	0.816***	(0.048)	0.816***	(0.048)	0.816***	(0.048)	0.816***	(0.048)
District 2[c]	1.016	(0.079)	1.004	(0.075)	1.008	(0.076)	0.992	(0.078)
District 3[c]	1.175	(0.100)	1.158	(0.096)	1.145	(0.094)	1.161	(0.097)
District 4[c]	1.198	(0.111)	1.179	(0.105)	1.162	(0.102)	1.186	(0.108)
District 5[c]	1.089	(0.084)	1.079	(0.080)	1.066	(0.079)	1.084	(0.082)
District 6[c]	0.988	(0.086)	0.967	(0.080)	0.958	(0.079)	0.976	(0.082)
District 7[c]	1.089	(0.097)	1.074	(0.092)	1.064	(0.093)	1.084	(0.094)
District 8[c]	1.157	(0100)	1.136	(0.092)	1.118	(0.090)	1.137	(0.095)
District 9[c]	1.107	(0.094)	1.084	(0.088)	1.076	(0.085)	1.083	(0.088)
Level 2 Variance	0.052***	(0.009)	0.052***	(0.009)	0.052***	(0.009)	0.051***	(0.009)
Constant	0.012***	(0.002)	0.013***	(0.002)	0.013***	(0.002)	0.013***	(0.002)
Observations	112,314	112,314	112,314	112,314	112,314	112,314	112,314	112,314
Number of groups	643	643	643	643	643	643	643	643

Robust standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$
[a] Larceny from Auto is reference group
[b] January is reference group
[c] District 1 is reference group
[d] 1st Quartile of Proportion Black is reference group
[e] 1st Decile of Proportion Black is reference group
SE=Robust standard errors clustered at the census tract

Bibliography

Andersen, T. S. (2015). Race, ethnicity, and structural variations in youth risk of arrest: Evidence from a national longitudinal sample. *Criminal Justice and Behavior*, *42*(9). https://journals.sagepub.com/doi/full/10.1177/0093854815570963?casa_token=Vz_d0gDvZmgAAAAA%3Aa8ESw7bDv1MH5eVPkRptPR2_9bI3kMXuBc1eydX2oJ4DIH-0uG8cUMQKJoc182XTOQDhvdWuwedwCg

Beardslee, J., Miltimore, S., Fine, A., Frick, P. J., Steinberg, L., & Cauffman, E. (2019). Under the radar or under arrest: How is adolescent boys' first contact with the juvenile justice system related to future offending and arrests? Law and Human Behavior, 43(4), 342–357. https://doi.org/10.1037/lhb0000340

Bercal, T. E. (1970). Calls for Police Assistance: Consumer Demands for Governmental Service. American Behavioral Scientist, 13(5–6), 681–691. https://doi.org/10.1177/000276427001300504

Bester, C. A., Conley, T. G., & Hansen, C. B. (2011). Inference with dependent data using cluster covariance estimators. Journal of Econometrics, 165(2), 137–151. https://doi.org/10.1016/j.jeconom.2011.01.007

Black, D. J. (1971). The Social Organization of Arrest. *Stanford Law Review*, *23*(6), 1087–1111. https://doi.org/10.2307/1227728

Blake, J. (2015, December 7). Why black political power isn't enough in Baltimore? CNN. https://www.cnn.com/2015/12/06/us/baltimore-black-political-power-freddie-gray-trial/index.html

Blalock, H. M. (1967). *Toward a Theory of Minority-group Relations*. Wiley.

Blauner, B. (1972). Racial Oppression in America. Harper & Row.

Boehme, H. M., Cann, D., & Isom, D. A. (2022). Citizens' perceptions of over- and under-policing: A look at race, ethnicity, and community characteristics. *Crime & Delinquency*, *68*(1), 123–154. https://doi.org/10.1177/0011128720974309

Baltimore Police Department. (n.d.). BPD Community Policing Plan. Retrieved February 28, 2024, from https://www.baltimorepolice.org/transparency/bpd-policies/10-bpd-community-policing-plan

Braga, A. A., Brunson, R. K., & Drakulich, K. M. (2019). Race, place, and effective policing. *Annual Review of Sociology*, *45*(1), 535–555. https://doi.org/10.1146/annurev-soc-073018-022541

Brooks-Gunn, J., Duncan, G. J., Klebanov, P. K., & Sealand, N. (1993). Do neighborhoods influence child and adolescent development? *American Journal of Sociology*, *99*(2), 353–395. https://doi.org/10.1086/230268

Brunson, R. K. (2020). Protests focus on over-policing. But under policing is also deadly. *Washington Post*.

Carter, D. L., & Carter, J. G. (2016). Effective Police Homicide Investigations: Evidence from Seven Cities With High Clearance Rates. Homicide Studies, 20(2), 150–176. https://doi.org/10.1177/1088767915576996

Chamlin, M. B., & Liska, A. E. (1992). Social structure and crime control revisited: The declining significance of intergroup threat. *In Social Threat and Social Control* (pp. 102–112). SUNY Press.

Chamlin, M. B., & Myer, A. J. (2009). Disentangling the crime-arrest relationship: The influence of social context. *Journal of Quantitative Criminology, 25*(4), 371–389. https://doi.org/10.1007/s10940-009-9072-z

Chamlin, M. B. (1987). General assistance among cities: an examination of the need, economic threat, and benign neglect hypotheses. *Social Science Quarterly, 68*(4), 834–846.

Chyn, E., & Katz, L. F. (2021). Neighborhoods matter: Assessing the evidence for place effects (Working Paper 28953). National Bureau of Economic Research. https://doi.org/10.3386/w28953

Clear, T. R. (2008). The Effects of High Imprisonment Rates on Communities. Crime and Justice, 37(1), 97–132. https://doi.org/10.1086/522360

Donovan, D. (2015, April 22). Brutality lawsuits continue in Baltimore, site of Freddie Gray death. Baltimore Sun. https://www.baltimoresun.com/maryland/bs-md-gray-police-lawsuits-20150422-story.html

Eitle, D., & Monahan, S. (2009). Revisiting the Racial Threat Thesis: The Role of Police Organizational Characteristics in Predicting Race-Specific Drug Arrest Rates. Justice Quarterly, 26(3), 528–561. https://doi.org/10.1080/07418820802427817

Eitle, D., D'Alessio, S. J., & Stolzenberg, L. (2002). Racial threat and social control: A test of the political, economic, and threat of black crime hypotheses. *Social Forces, 81*(2), 557–576. https://doi.org/10.1353/sof.2003.0007

Feldmeyer, B., & Cochran, J. C. (2018). Racial threat and social control: a review and conceptual framework for advancing racial threat theory. *In Building a Black Criminology* (Vol. 24). Routledge.

Feldmeyer, B., & Ulmer, J. T. (2011). Racial/Ethnic Threat and Federal Sentencing. Journal of Research in Crime and Delinquency, 48(2), 238–270.

Frey, W. H. (2020, July 1). The nation is diversifying even faster than predicted, according to new census data. Brookings. https://www.brookings.edu/articles/new-census-data-shows-the-nation-is-diversifying-even-faster-than-predicted/

Gaston, S. (2019). Producing race disparities: A study of drug arrests across place and race. Criminology, 57(3), 424–451. https://doi.org/10.1111/1745-9125.12207

Hartmann, M. (2015, April 30). Freddie Gray Protests Spread Across the Country With Thousands Marching Against Police Brutality. *Intelligencer*. https://nymag.com/intelligencer/2015/04/freddie-gray-protests-spread-across-the-country.html

Hasenfeld, Y. (2000). Organizational forms as moral practices: The case of welfare departments. *Social Service Review*, 74(3), 329–351. https://doi.org/10.1086/516408

Hox, J. (1998). Multilevel Modeling: When and Why. In I. Balderjahn, R. Mathar, & M. Schader (Eds.), Classification, Data Analysis, and Data Highways (pp. 147–154). Springer. https://doi.org/10.1007/978-3-642-72087-1_17

Huff, J. (2021). Understanding police decisions to arrest: the impact of situational, officer, and neighborhood characteristics on police discretion. *Journal of Criminal Justice, 75*, 101829. https://doi.org/10.1016/j.jcrimjus.2021.101829

Investigation of the Baltimore City Police Department. (2016). U.S. Department of Justice Civil Rights Division.

Jackson, J., McKay, T., Cheliotis, L., Bradford, B., Fine, A., & Trinkner, R. (2023). Centering race in procedural justice theory: Structural racism and the under- and overpolicing of Black communities. *Law and Human Behavior*, *47*(1), 68–82.

Kahn, K. B., & Davies, P. G. (2017). What influences shooter bias? The effects of suspect race, neighborhood, and clothing on decisions to shoot. *Journal of Social Issues, 73*(4), 723–743. https://doi.org/10.1111/josi.12245

Kane, R. J., Gustafson, J. L., & Bruell, C. (2013). Racial Encroachment and the Formal Control of Space: Minority Group-Threat and Misdemeanor Arrests in Urban Communities. Justice Quarterly, 30(6), 957–982. https://doi.org/10.1080/07418825.2011.636376

Kirk, D. S., & Matsuda, M. (2011). legal cynicism, collective efficacy, and the ecology of arrest. *Criminology*, *49*(2), 443–472. https://doi.org/10.1111/j.1745-9125.2011.00226.x

Kirk, D. S. (2008). The neighborhood context of racial and ethnic disparities in arrest. Demography, 45(1), 55–77. https://doi.org/10.1353/dem.2008.0011

Klinger, D. A. (1997). Negotiating Order in Patrol Work: An Ecological Theory of Police Response to Deviance*. Criminology, 35(2), 277–306. https://doi.org/10.1111/j.1745-9125.1997.tb00877.x

Levchak, P. J. (2017). Do Precinct Characteristics Influence Stop-and-Frisk in New York City? A Multi-Level Analysis of Post-Stop Outcomes. Justice Quarterly, 34(3), 377–406. https://doi.org/10.1080/07418825.2016.1162320

Lewis, C., & Usmani, A. (2022). The injustice of under-policing in America. American Journal of Law and Equality, 2, 85–106. https://doi.org/10.1162/ajle_a_00030

Light, M. T., & Ulmer, J. T. (2016). Explaining the gaps in White, Black, and Hispanic violence since 1990: Accounting for immigration, incarceration, and inequality. *American Sociological Review, 81*(2). https://journals-sagepub-com.proxy-um.researchport.umd.edu/doi/full/10.1177/0003122416635667

Liska, A. E., & Chamlin, M. B. (1984). Social structure and crime control among macrosocial units. *American Journal of Sociology, 90*(2), 383–395. https://doi.org/10.1086/228084

Liska, A. E., Chamlin, M. B., & Reed, M. D. (1985). Testing the economic production and conflict models of crime control. *Social Forces*, *64*(1), 119–138. https://doi.org/10.1093/sf/64.1.119

Liska, A. E., Lawrence, J. J., & Benson, M. (1981). Perspectives on the legal order: the capacity for social control. *American Journal of Sociology, 87*(2), 413–426. https://doi.org/10.1086/227465

Liska, A. E. (1992). *Social Threat and Social Control*. SUNY Press.

Ludwig, J., Duncan, G. J., Gennetian, L. A., Katz, L. F., Kessler, R. C., Kling, J. R., & Sanbonmatsu, L. (2013). Long-term neighborhood effects on low-income families: Evidence from moving to opportunity. *American Economic Review, 103*(3), 226–231. https://doi.org/10.1257/aer.103.3.226

Lum, C. (2011). The influence of places on police decision pathways: From call for service to arrest. *Justice Quarterly, 28*(4), 631–665. https://doi.org/10.1080/07418825.2010.526130

Marier, C. J., & Fridell, L. A. (2023). Racial Threat and Punitive Police Attitudes. *Justice Quarterly,* 40(6), 859–884. https://doi.org/10.1080/07418825.2022.

Mennerick, L. A. (1974). Client Typologies: A Method of Coping With Conflict in the Service Worker-Client Relationship. Sociology of Work and Occupations, 1(4), 396–418. https://doi.org/10.1177/073088847400100403

Midgett & LaFree. Working Paper. Civilian and Police Decision-Making after a High-Profile Case of Police Violence.

Moyer, R. A. (2022). The effect of a death-in-police-custody incident on community reliance on the police. *Journal of Quantitative Criminology, 38*(2), 459–482. https://doi.org/10.1007/s10940-021-09504-x

Mozingo, J., & Phelps, T. M. (2015, April 29). Black power in Baltimore: When African American leaders confront racial unrest. Los Angeles Times. https://www.latimes.com/nation/la-na-black-power-20150429-story.html

Myer, A. J., & Chamlin, M. B. (2011). Aggregation bias and the benign neglect hypothesis. *Journal of Crime and Justice*, *34*(2), 124–138. https://doi.org/10.1080/0735648X.2011.580512

New Racial Segregation Measures for States and Large Metropolitan Areas: Analysis of the 2005-2009 American Community Survey. (n.d.). Retrieved January 3, 2023, from https://censusscope.org/ACS/Segregation.html

Osgood, D. W., & Anderson, A. L. (2004). Unstructured socializing and rates of delinquency. Criminology, 42(3). https://onlinelibrary-wiley-com.proxy-um.researchport.umd.edu/doi/abs/10.1111/j.1745-9125.2004.tb00528.x

Ousey, G. C., & Lee, M. R. (2008). Racial disparity in formal social control: An investigation of alternative explanations of arrest rate inequality. *Journal of Research* *in Crime and Delinquency*, *45*(3), 322–355. https://doi.org/10.1177/0022427808317575

Parker, K. F., Stults, B. J., & Rice, S. K. (2005). Racial threat, concentrated disadvantage and social control: Considering the macro-level sources of variation in arrests. *Criminology, 43*(4), 1111–1134. https://doi.org/10.1111/j.1745-9125.2005.00034.x

Peck, J. H., & Elligson, R. L. (2021). Race, Ethnicity, and Police–Community Relations. In Oxford Research Encyclopedia of Criminology and Criminal Justice. https://doi.org/10.1093/acrefore/9780190264079.013.338

Peterson, P. & Krivo, L. (2010). *Divergent Social Worlds*. Russell Sage Foundation.

Raaphorst, N., & Van de Walle, S. (2018). A signaling perspective on bureaucratic encounters: how public officials interpret signals and cues. *Social Policy & Administration, 52*(7), 1367–1378. https://doi.org/10.1111/spol.12369

Sampson, R. J., Morenoff, J. D., & Gannon-Rowley, T. (2002). Assessing "neighborhood effects": social processes and new directions in research. *Annual Review of Sociology, 28*(1), 443–478.

Smith, D. A. (1986). The neighborhood context of police behavior. *Crime and Justice, 8*, 313–341.

Smith, J. (2021). Racial threat and crime control: integrating theory on race and extending its application. *Critical Criminology*, *29*(2), 253–271. https://doi.org/10.1007/s10612-019-09485-1

Smith, D. A., Visher, C. A., & Davidson, L. A. (1984). Equity and Discretionary Justice: The Influence of Race on Police Arrest Decisions Criminology. Journal of Criminal Law and Criminology, 75(1), 234–249.

Snipes, J. B., Bernard, T. J., & Gerould, A. L. (2019). *Vold's Theoretical Criminology (8th ed.).* https://global.oup.com/ushe/product/volds-theoretical-criminology-9780190940515

Spitzer, S. (1975). Toward a Marxian Theory of Deviance. Social Problems, 22(5), 638–651. https://doi.org/10.2307/799696

stata.com. (n.d.). melogit—Multilevel mixed-effects logistic regression.

Stolzenberg, L., D'alessio, S. J., & Eitle, D. (2004). A multilevel test of racial threat theory. *Criminology*, *42*(3), 673–698. https://doi.org/10.1111/j.1745-9125.2004.tb00533.x

Stucky, T. D. (2012). The Conditional Effects of Race and Politics on Social Control: Black Violent Crime Arrests in Large Cities, 1970 to 1990. Journal of Research in Crime and Delinquency, 49(1), 3–30. https://doi.org/10.1177/0022427810393020

Stults, B. J., & Baumer, E. P. (2007). Racial Context and Police Force Size: Evaluating the Empirical Validity of the Minority Threat Perspective. American Journal of Sociology, 113(2), 507–546. https://doi.org/10.1086/518906

Sunshine, J., & Tyler, T. R. (2003). The Role of Procedural Justice and Legitimacy in Shaping Public Support for Policing. Law & Society Review, 37(3), 513–547. https://doi.org/10.1111/1540-5893.3703002

Terrill, W., & Reisig, M. D. (2003). Neighborhood context and police use of force. *Journal of Research in Crime and Delinquency*, *40*(3), 291–321. https://doi.org/10.1177/0022427803253800

Turk, A. T. (1969). Criminality and Legal Order. Rand McNally.

Uggen, C., Vuolo, M., Lageson, S., Ruhland, E., & K. Whitham, H. (2014). The Edge of Stigma: An Experimental Audit of the Effects of Low-Level Criminal Records on Employment. Criminology, 52(4), 627–654. https://doi.org/10.1111/1745-9125.12051

US Census Bureau. (2023, December 7). American Community Survey 5-Year Data (2009-2022). Census.Gov. https://www.census.gov/data/developers/data-sets/acs-5year.html

U.S. Census Bureau. (2020). U.S. Department of Commerce. https://data.census.gov/

US Department of Justice. (2017). *Federal Officials Decline Prosecution in the Death of Freddie Gray* (Press Release 17–999). https://www.justice.gov/opa/pr/federal-officials-decline-prosecution-death-freddie-gray

Varano, S. P., Schafer, J. A., Cancino, J. M., & Swatt, M. L. (2009). Constructing crime: neighborhood characteristics and police recording behavior. *Journal of Criminal Justice*, *37*(6), 553–563. https://doi.org/10.1016/j.jcrimjus.2009.09.004

Vélez, M. B., & Peguero, A. A. (2023). LatCrit and Criminology: Toward a Theoretical Understanding of Latino/a/x Crime and Criminal Legal System Involvement. Annual Review of Criminology, 6, 307–338. https://doi.org/10.1146/annurev-criminol-030920-120002

Vélez, M. B., Lyons, C. J., & Santoro, W. A. (2015). The Political Context of the Percent Black-Neighborhood Violence Link: A Multilevel Analysis. Social Problems, 62(1), 93–119. https://doi.org/10.1093/socpro/spu005

Vogt, P. W., Vogt, E. R., Gardner, D. C., & Haeffele, L. M. (2014). *Advanced Associational Methods. In Selecting the Right Analyses for Your Data: Quantitative, Qualitative, and Mixed Methods*. Guilford Press.

Weisburd, D., White, C., & Wooditch, A. (2020). Does collective efficacy matter at the micro geographic level?: findings from a study of street segments. *The British Journal of Criminology, 60*(4), 873–891. https://doi.org/10.1093/bjc/azaa007

Weitzer, R., Tuch, S. A., & Skogan, W. G. (2008). Police–Community Relations in a Majority-Black City. Journal of Research in Crime and Delinquency, 45(4), 398–428. https://doi.org/10.1177/0022427808322617

Werthman, C., & Piliavin, I. (1967). Gang Member and the Police. In The Police: Six Sociological Essays. https://www.ojp.gov/ncjrs/virtual-library/abstracts/police-six-sociological-essays

Wilson, W. J. (2012). The Truly Disadvantaged. University of Chicago Press Economics Books. https://ideas.repec.org//b/ucp/bkecon/9780226901268.html

Wooldredge, J. (2002). Examining the (ir)relevance of Aggregation Bias for Multilevel Studies of Neighborhoods and Crime with an Example Comparing Census Tracts to

Official Neighborhoods in Cincinnati*. Criminology, 40(3), 681–710.

https://doi.org/10.1111/j.1745-9125.2002.tb00970.

Yan, H., & Ford, D. (2015, April 28). Baltimore protests turn violent; police injured. *CNN*.

https://www.cnn.com/2015/04/27/us/baltimore-unrest/index.html