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Proactive or Predetermined?: Contextualizing Color-Blind Policing Practices in New York City

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PROACTIVE OR PREDETERMINED?: CONTEXTUALIZING COLOR-BLIND
POLICING PRACTICES IN NEW YORK CITY

By

Rachel E. Lautenschlager

A THESIS

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PROACTIVE OR PREDETERMINED? CONTEXTUALIZING COLOR-BLIND
POLICING PRACTICES IN NEW YORK CITY

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Proactive or Predetermined?: Contextualizing
Color-Blind Policing Practices in New York City

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        Since the widespread growth of proactive policing strategies across the United

States during the 1990s, community members and scholars alike have critiqued these law

enforcement techniques for their injurious effects on minority communities. Prior

research has established that suspect and neighborhood characteristics influence police

decision making and stop outcomes, with Blacks and Latinos faring worse than their

White counterparts. What remains largely unknown, however, are the underlying

mechanisms driving these disparities. This study approaches the problem by conducting a

neighborhood-level analysis of the reasons that police officers provided for making 4.5

million stops over a period of twelve years as a part of the New York City Police

Department's stop and frisk policy. Specifically, this analysis examines how the

proportions of stops that are made based on appearance varies depending on

neighborhood racial and ethnic composition and perceived crime rates. The results

indicate that nonbehavioral stop rates are significantly higher in Black and Latino

neighborhoods, and that perceived crime is one of the strongest predictors of the

proportion of stops in a neighborhood that are made for nonbehavioral reasons. The

findings of this study advance the literature on policing by providing evidence that neighborhood characteristics are salient factors in determining policing practices.

Dedication

This thesis is dedicated to my grandparents, Martin and Rita Kades. Thank you for

teaching me the infinite importance of kindness and justice

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First and foremost, I would like to thank Dr. Marisa Omori, my advisor and committee chair. You helped me cultivate this project from the very beginning, and believed in me even when my R^2 equaled a mere 0.02. I am grateful for not only the time you committed to editing and revising, but all of the insightful comments you shared with me along the way. Because of your guidance, this thesis is something I can be proud of.

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Finally, a huge thank you to my parents for always encouraging my academic pursuits. Had I not majored in Judaic studies, I am not sure I would be a criminologist today.

TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

Chapter 1: Introduction

The increasing prominence of proactive policing in the United States since the 1990s has been accompanied by concerns about the racially inequitable outcomes of such tactics. Following these tactics, police officers stop individuals on the street for breaking minor, low level crimes, or sometimes for simply looking suspicious. This issue has recently grown more acute with the onslaught of highly publicized deaths of Black people at the hands of police officers, after being stopped under such seemingly innocuous circumstances. Despite repeated assurances by criminal justice officials of the "color-blindness" of their institutional policies, communities of color are disproportionately policed, even when taking into account race and ethnic group crime involvement (Engel and Calnon 2004) and the geographic distribution of crime (Geller and Fagan 2010).

In a Washington Post opinion piece published during the summer of 2013, then mayor of New York City Michael Bloomberg disputed allegations of racial profiling by the New York City Police Department. Specifically, he criticized United States District Court Judge Shira Scheindlin's recent ruling that deemed the Department's stop-and-frisk tactics unconstitutional. Arguing that stops are made on the basis of behavior rather than race, ethnicity, or other physical characteristics, Bloomberg contended that police were "stopping people in those communities who fit descriptions of suspects or are engaged in suspicious activity...If an officer sees someone acting in a manner that suggests a crime is afoot, he or she has an obligation to stop and question that person" (2013). While this explanation matches the rhetoric of decades of judicial decisions regarding the constitutionality of forcible stops and may describe official Department policy, it leaves

unresolved critical questions regarding who fits the description of a suspect, what constitutes suspicious activity, and the role that context plays in determining these factors. Although stop and frisk rates have decrased appreciably since the 2013 ruling, proactive policing remains a prominent element of law enforcement in New York City. Stop and frisk policing instituted in other American cities, including Philadelphia, Chicago, and Los Angeles, has been critiqued on similar grounds, making the answers to these questions consequential far beyond the boundaries of New York City (James 2015). That the same problems have arisen around the country suggests that stop and frisk policies are not simply a practical problem, but bring to the forefront substantial theoretical questions about the role of police in nonwhite communities.

In order to better understand the social and institutional mechanisms leading to these disparities, we must untangle the often convoluted relationships between race and ethnicity, space, police decision making, and the legal apparatus that provides the guidelines within which policing agencies must conduct themselves. This study approaches the problem through an investigation of New York City's contemporary proactive "stop-and-frisk" policing approach. Building on prior research analyzing the influence of suspect characteristics on police discretion, the effect of neighborhood characteristics on policing outcomes, and the criminalization of race, ethnicity, and space, this study examines how neighborhood context influences the reasons that officers provide for stopping suspects. A major contribution of this research is using neighborhoods as the unit of analysis, which allows for a departure from the traditional policing literature, which tends to examine individual stops. Furthermore, I situate this investigation within the broader organizational environment by exploring how the

Supreme Court opened a pathway to legalized racial profiling and how this legal framework shaped the official policies of the NYPD. Specifically, I will address the following series of questions:

1. How do the racial and ethnic compositions of a neighborhood influence the rate of stops?

2. How do the racial and ethnic compositions of a neighborhood influence the proportion of non-behavioral stops (i.e. stops that are conducted based on a suspect's appearance rather than his/her behavior)?

3. How is the effect of racial and ethnic composition on the proportion of non-behavioral stops conditioned by police officers' perceptions of neighborhood crime?

4. How do neighborhood racial and ethnic compositions affect the proportion of behavioral and non-behavioral stops that are "successful"?

The chapters of this thesis proceed as follows. Chapter 2 provides a legal and historical background of stop and frisk in New York City in order to situate this study in the appropriate context. The chapter closes with a review of the extant literature of stop and frisk policing in New York City. Chapter 3 consists of a review of the literature on which this study is based. The literature is broken into three categories: suspect characteristics and police discretion, neighborhood characteristics and policing outcomes, and the criminalization of race and space. The chapter closes with a discussion of the contributions of this study and a statement of the hypotheses that will be tested. Chapter 4 outlines the methods that will be used in conducting the analyses. I describe each of the data sources, the operationalization of the variables, and, finally, the analytical techniques

and models. Chapter 5 reviews the findings of each of the neighborhood-level analyses.

The final chapter consists of a discussion of the findings, policy implications, and

avenues for future research.

Chapter 2: Background

This chapter puts this study into context by providing an overview of the legal and historical background of stop and frisk policing in New York City. I begin by reviewing the constitutional foundation of stop and frisk policing, and emphasize two Supreme Court cases that are especially consequential for this analysis. The next section provides a description of the NYPD through an organizational perspective, with an emphasis on how police professionalization served as an impetus towards large-scale stop and frisk policing. Finally, I review the empirical research on stop and frisk policing in New York City in order to set a foundation for the study at hand.

The Constitutionality of Stop and Frisk

Critics of stop and frisk often point fingers at policing agencies who implement such procedures, without acknowledging that stop and frisk is a law enforcement strategy that has repeatedly passed the approval of the United States Supreme Court, as demonstrated in the many favorable rulings over the past half century (Del Carmen 2010; Hutchins 2013). Although local police departments do have immense agency in deciding how to exercise their authority (Beckett 2012), it is critical to accurately situate them within the context of the legal world. This is important because court decisions can and do impact law enforcement practices (Klinger 2004). Although there have been many cases over the years addressing stop and frisk specifically, two Supreme Court cases in particular have significant consequences for this study: *Terry v. Ohio* (1968) and *Illinois v. Wardlow* (2001).

Fundamental to any discussion of police discretion in conducting stop and frisks is an acknowledgement of the extent of their legal authority in this domain, as prescribed

by the United States Supreme Court. The case of most relevance to the analysis at hand is *Terry v. Ohio* (1968). Although the Court adamantly maintained that the particularities of the case did not allow them to make a ruling regarding the powers of police to stop individuals when probable cause is absent, that ruling has since served as the foundation for analyzing the constitutionality of police stops. Two elements of this decision are of particular importance. First, by differentiating a stop from an arrest, the Court determined that probable cause need not be demonstrated to justify a stop. Throughout the decision they elaborate on this lesser burden of evidence, which came to be known as reasonable suspicion, which need only be evidenced by "articulable facts" of the situation. However, four decades later, the minimum degree of certainty necessary to conduct a stop remains an elusive marker (Del Carmen 2010), allowing for immense discretion on the part of police. Second, the Court has shown repeatedly deference to the decisions that patrol officers make based on their accumulated training and experience. In so doing, they affirmed the constitutional right of police to use wide discretion when patrolling the streets with only limited fear of repercussion. Despite the right afforded to police officers to exercise immense discretion when conducting stops, researchers have discovered evidence that stops of minority individuals frequently do not meet constitutional standards (Fagan and Davies 2000; Bellin 2014). Ultimately, the Supreme Court's ruling in *Terry v. Ohio* established that the constitutionality of any stop and frisk policy is fundamentally tied to the reasons that police officers provide for stopping suspects.

Because neighborhood characteristics are a focal concern of this analysis, a second Supreme Court decision is worthy of acknowledgement. In *Illinois v. Wardlow* (2000), the Supreme Court substantiated the use of neighborhood characteristics as a

valid factor to consider when establishing reasonable suspicion. The Court determined that the behavior of fleeing from the police does not in itself provide sufficient evidence to warrant reasonable suspicion. However, they concluded that fleeing from police *within a high-crime area* does justify the formation of reasonable suspicion. By not only establishing this neighborhood condition as a valid reason for choosing to stop someone, but allowing it to serve as the factor that enables officers to surmount the burden of reasonable suspicion, the Supreme Court transformed people who live and work in high-crime areas into easy targets for police stops. Given the widely acknowledged correlations between race, poverty and violent crime in the United States, and that these phenomena tend to be clustered in space, policing agencies are thus provided a legal incentive to focus their efforts on poor, minority communities.

Although this study is not a test of constitutionality, the decisions made by the Supreme Court in *Terry v. Ohio* and *Illinois v. Wardlow* make salient the need to examine the reasons that officers provide for stopping suspects and the settings in which stops are occurring. When analyzing policing practices, it is critical to keep in mind that the policies designed and implemented by local law enforcement agencies are guided by Court decisions such as these. Furthermore, it is important to note that the 2013 ruling in *Floyd v. the City of New York*, in which the NYPD's implementation of stop and frisk was deemed unconstitutional, seems to have had a major impact on how the policy is wielded. While there were over half-a-million stops recorded during 2012, that number decreased to 23,000 recorded stops in 2015 (New York Civil Liberties Union). This transformation is suggestive of the organizational power of the NYPD. Rather than focusing on individual officers or incidents, some researchers have tried to understand

policing through organizational theories. This perspective will be discussed in the next section.

An Organizational Perspective of the NYPD

As described in the previous section, police departments are low-level law enforcement agency that have rules and regulations imposed upon them. At the same time, however, police officers have a unique capacity to influence how those rules and regulations are implemented in the real world. Lipsky (1980) articulated this phenomenon in his theory of street-level bureaucracies, which he believed applied to police, as well as to other individuals working at the street level to deliver social services. In the process he describes, the individual-level decisions of police officers in their day-to-day work cumulatively obtain social significance, and in this way shape the realization of policy, if in an ad hoc manner. Although a precinct commander may instruct his or her patrol officers to conduct stop and frisk in a lawful manner, it is the patrol officers who must figure out how to accomplish that in the real world situations that they encounter on a daily basis. Thus, adaptation to professional constraints is one of the main mechanisms through which police determine the face of policy. This process is codified each time a court reifies an officer's reason for conducting a stop, such as in *Wardlow*.

However, to imagine patrol officers as autonomous, rule-making agents would be mistaken. Hagan (1989) argues that proactive policing, such as that engaged in by the NYPD, necessitates that law enforcement actors cooperatively rely on one another. For example, because proactive policing involves seeking out potential criminals, rather than responding to crimes after they have occurred, a patrol officer will likely only stop people in situations that he or she believes his/her supervisors will agree are appropriate, in order

to avoid getting in trouble. Applying the street-level bureaucracy theory to stop and frisk in New York City, Portillo and Rudes (2014) argue that discretion does not result in every stop being handled in an individualized, ad hoc manner. Rather, organizational practices are internalized and serve as the basis for the formation of routines that officers exercise on the streets. While patrol officers are the ones who ultimately determine how stop and frisk is implemented, they are still products of the professional organizations for which they work.

The notable role that departmental policy plays in shaping the behavior of individual officers was demonstrated in the early 1970s, when the NYPD placed additional constraints on the circumstances considered appropriate for the use of deadly force. The number of shootings by police dropped immediately (Rostker, Hanser, Hix, Jensen, Morral, Ridgeway and Schell 2008). The depiction of the NYPD as a bureaucracy became especially relevant in the early 1990s, when the agency transitioned to a "business performance management" model of operations (Eterno and Silverman 2012). From this point forward, the actions of on-duty patrol officers were influenced not only by prior experience and the situations they encountered on a day-to-day basis, but also by managerial pressure to meet the expectations set forth by the CompStat program[1]. Through this transition, the face of policing in New York City changed dramatically. The introduction of big data as a part of everyday policing brought with it a new focus for the NYPD. The new goals of the department did not involve individual or community

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[1] CompStat (short for compare statistics) is a managerial tool developed to aid in crime reduction by systematically collecting and mapping crime data, which allows the police organization to more easily identify "problem areas." CompStat was adopted by the NYPD in 1994, under the direction of Police Commissioner William J. Bratton, placing more pressure than ever on precinct captains to keep crime numbers down. The extent to which CompStat contributed to the subsequent drop in crime throughout New York City has been a matter of fierce debate among academics, practitioners, and policymakers alike.

rehabilitation, but rather viewed crime as a problem to be reigned-in and managed, through a strategy popularly known as order maintenance policing (Kelling and Coles 1998). The primary targets of order maintenance policing were poor, minority communities (Weisburd, Telep, and Lawton 2014). These communities earned the permanent labels of "problem people" and "problem places" that needed to be managed, through forceful policing, for the "good of the city" (Feeley and Simon 1992).

Despite evidence of a strong and influential internal culture constructed around an edifice of solidarity and a shared familiarity with confronting danger (Roy 2009), analyses of stop-and-frisk outcomes in New York City often fail to acknowledge the organizational and professional context in which officers conduct their work. Although this study does not test these factors, to capture the idea that NYPD officers are acting as members of larger organizations, I orient my study away from the focus on decisions and behaviors of individual officers by analyzing decision making at an aggregate level. This methodology is also in line with Lipsky's (1980) description of street-level bureaucracies, as the power he ascribes to police as policy-makers only arises in the aggregate effect of their decisions.

Thus far, this chapter has supplied a legal and historical background to impart a context that is important for understanding how the policy of stop and frisk is designed and implemented. In the next section, I will provide an overview of recent research findings regarding the racially disparate outcomes of the policy in New York City.

Stop and Frisk in New York City

Since stop and frisk data became publicly available in the mid-2000s, a number of studies have been conducted that demonstrate the racially inequitable design of New

York City's policy. At the individual level, Blacks are disproportionately the targets of pedestrian stops when compared to their total population in New York City (Evans, Maragh, and Porter 2014). This remains true when using racial and ethnic group crime participation rates as the benchmark against which stop rates are compared (Gelman, Fagan, and Kiss 2007). Blacks are not only the most frequently stopped, but they are also most likely to be frisked, searched, forcefully treated and receive further punishment (Ferrandino 2014). Such findings are especially notable given that stop and frisk is a proactive policing strategy, meaning that officers are attempting to prevent crime by identifying people who are likely to engage in illegal activity, rather than reacting to crimes after they occur. Studying stops, then, is more accurately understood as an examination of police behavior, rather than a measure of crime (Lynch 2012). As such, understanding the role of neighborhood context in determining the trajectory of a pedestrian stop may provide insight into how officers identify suspicious individuals and behavior.

A related body of research has examined outcomes of stop and frisk in New York City at the precinct or neighborhood level. The results of these studies generally mirror the racial and ethnic discrepancies found at the individual level. At a foundational level, stop and frisk rates are highest in areas with high rates of non-white residents (Evans et al 2014), and this is especially true when considering predominantly Black neighborhoods (Ferrandino 2014). Marijuana stops are not only concentrated in non-white neighborhoods, but this relationship continues to hold true even when controlling for socioeconomic indicators and local crime levels (Geller and Fagan 2010). Furthermore, the inter-neighborhood discrepancies in stop and frisk rates based on racial and ethnic

makeup has grown over time (Fagan, Geller, Davies, and West 2009), which may signal increased targeting of predominantly minority areas. Finally, New York City data provide evidence that Black and Latino persons are especially likely to be stopped when in a predominantly white neighborhood (Gelman et al 2007; Ferrandino 2014). These findings suggest that a suspect may be viewed differently by police, depending on the ecological context in which he or she is spotted or stopped.

From the extant body of research on stop and frisk policing in New York City presented here, it is clear that, intended or not, racially disparate outcomes are a prevalent consequence of the policy. Having established that this is the case, few studies have subsequently tried to determine the driving force behind this unequal treatment. The repeated findings that stop and frisk outcomes are worse for Black and Latino residents and neighborhoods even when controlling for crime participation rates, crime rates, and socioeconomic measures, suggest that that there are other social mechanisms at play. This study begins answering the question of what those mechanisms are. By connecting aggregated explanations of why officers choose to conduct stops with the characteristics of the neighborhoods in which those stops occur, I am able to explore how race, ethnicity, and perceptions of criminality are related on a larger scale.

Chapter Summary

To understand any analysis of stop and frisk policing, it is integral to understand the context in which it is taking place. To that end, in this chapter I provide an overview of legal and organizational background information to New York City's stop and frisk policy and practices. First, I discussed the constitutionality of stop and frisk as an organizational policy. The ruling in *Terry* illustrated the Court's deference to police

officers in determining the appropriate circumstances for making stops, and, importantly, lowered the standard of evidence necessary to make a stop constitutional. Additionally, in *Wardlow*, the Court upheld the identification of a neighborhood as "high-crime" as a constitutionally acceptable reason for stopping someone. In doing so, they thus implicated neighborhood characteristics more broadly in this decision making process. Next, I provided an organizational perspective of the NYPD. I suggested that although patrol officers are the final decision makers in determining when a stop will occur, they are ultimately members of a broader organization, whose norms to which they are bound. By expounding that police officers are acting within organizational constraints, and that police departments act within legal constraints, these two sections together provide an impetus for conducting an analysis at the aggregate level. Finally, I reviewed the extant literature on stop and frisk policing in New York City, which routinely finds evidence of racially and ethnically disparate outcomes, at both the individual and neighborhood level. As noted above, few studies focused on New York City have attempted to uncover the driving mechanisms of these racialized differences.

Chapter 3: Review of the Literature on Policing

The foundation of this study draws from the synthesis of three distinct literatures. First, the effects that suspect characteristics have on police discretion are examined through micro-level research on pedestrian stops, which provides insight into factors that influence an officer's decision to stop and frisk a particular suspect. Second, I explore the role that neighborhood characteristics play in determining police behavior and shaping the types of suspicion that are formed by police. For the purpose of this study, I am primarily interested in the role that racial and ethnic composition play, and how the experiences of Black and Latino communities may differ from White communities, as well as from one another. Finally, I review a budding line of research that investigates the implications of the criminalization of particular race and ethnic groups and the spaces in which they live and work. The varying levels of analysis implicated across these literatures--suspect characteristics are analyzed at the micro-level, whereas neighborhood characteristics and the racialization of space capture macro-level processes--allow us to integrate the interlocking sociological forces at work in the operation of proactive policing.

Suspect Characteristics and Police Discretion

Because the decision to conduct a pedestrian stop is ultimately made at the level of an individual patrol officer (Bittner 1967; Bass 2001), issues related to police discretion are a key component to understanding disparities in stop rates across the population. Although this study involves an analysis of neighborhoods, and does not consider the characteristics of individual suspects, it is nonetheless important to acknowledge this literature. First, studies that examine the effect of suspect

characteristics are, by far, the most common in the policing literature. Second, again invoking Lipsky's (1980) theory of street-level bureaucrats, it is reasonable to believe that the decisions that individual officers make during specific stops can apply at an aggregate level as well. If bias against minorities is occurring at an individual level, it is likely that these same processes are taking place more broadly.

One well established area of research has supplied strong evidence that suspect characteristics, especially race and ethnicity, are significant predictors of police decision making during stops (Kochel, Wilson, and Mastrofski 2011). Because it is difficult to measure the split-second decisions that officers make on the job, some researchers have attempted to replicate police work in a lab setting. Studies that simulate shooting situations reveal that police officers and civilians alike are quicker to "shoot" armed Black suspects than they are armed White or Latino suspects; at the same time, respondents were quicker to indicate "don't shoot" in the case of an unarmed White suspect (Sadler, Correll, Park, and Judd 2012; Senholzi, Depue, Correll, Banich, and Ito 2015). Racial bias was additionally present in response times towards Latino suspects compared to their white counterparts. It is a difficult, if not impossible, task to decipher whether and to what extent such differences in police behavior are due to conscious or subconscious decision making. Evincing the latter are empirical findings suggesting that, similar to the population more generally, police officers hold psychologically embedded associations between people of color and crime, of which they are likely unaware (Eberhardt, Goff, Purdie and Davies 2004). It is easy to imagine how such subconscious linkages might influence the trajectory of a police stop, during which officers must think and act on their feet, and, at times, make split-second decisions.

Other researchers have utilized administrative data to demonstrate racially disparate outcomes in stops of both pedestrians and vehicles. One such study discovered that Black motorists were more likely than either White or Hispanic drivers to be arrested, have their vehicle towed, be searched, or have a record check conducted (Alpert, Dunham, and Smith 2007). Comparing probabilities of frisks and searches during motor vehicle stops, Carroll and Gonzalez (2014) find that Blacks are more likely than whites to receive both. Furthermore, the discrepancy is greater in the case of frisks, which, given that the decision to frisk an individual is made more speedily than the choice to search them, provides support for the existence of implicit bias processes. Some studies suggest that the standards applied by police in determining when to initiate a stop are lower for minorities than whites, and that they may depend more heavily on subjective indicators of delinquency. Specifically, several researchers have come to the conclusion that, despite higher search rates, drug paraphernalia and weapons are equally or less likely to be found on (or in the car of) minority individuals (Engel and Calnon 2004; Engel and Johnson 2006; Gumbhir 2007; Ryan 2015). Such findings indicate that minority individuals are perceived as relatively more suspicious than are their white counterparts.

Research also indicates that suspects' appearances are important in terms of when and what kind of suspicion is formed. An observational study of police thought processes concluded that while in most cases behavior was the primary cause of suspicion, the majority of individuals who provoked suspicion were minorities and officers were more likely to form suspicion based on appearance in instances where the suspect was Black (Alpert, Dunham, Stroshine, Bennett and MacDonald 2004; Alpert, MacDonald and Dunham 2005; Dunham, Alpert, Stroshine and Bennett 2005). Additionally, nearly two-

thirds of officers in their study claimed that a suspect's appearance was a medium or high priority in developing suspicion. Given these findings, it seems plausible that suspects' appearances and how they are perceived by police may provide insight into the processes through which an allegedly color-blind policy can result in such immense racial and ethnic disparities. Because a suspect's actions are supposed to provide the motive for police intervention, differentiating between the circumstances under which behavioral and non-behavioral stops are initiated allows for an exploration of the unarticulated racial and ethnic impetus behind allegedly color-blind policies.

As is evident from this review, there is an expansive body of literature examining the relationship between suspect race and police discretion. However, it should be noted that much of this research has been conducted within the context of a "Black-White paradigm" (Martinez 2010), ignoring the unique experiences of Latinos and often leaving them out of studies entirely. As a result, there is a lack of literature addressing interactions between Latinos and police (Martinez 2007), which has made it difficult to assess this relationship. Studies that do analyze the effect of policing on Latinos have resulted in mixed findings, with some studies concludig that Latinos have worse outcomes than their White counterparts, and others finding no significant difference. However, it is salient to point out that the experiences that Latinos have with police are unique, especially given the growing overlap between immigration enforcement and crime control (Pickett 2016). In conflating Latino ethnicity with illegality, the appearance of being Latino not only becomes an indicator of potential criminality, but for police legitimizes their authority to question a person's reason for being somewhere (Romero

2005; Romero 2006). The consequences of policing for Latino communities will be addressed further in the next section.

Although this study is not an analysis of individual suspect characteristics, the findings presented here provide a critical context for a neighborhood-level analysis. Taken together, this body of research provides strong evidence that racial biases are common and persisting in police-citizen interactions. In the next section, I discuss how neighborhood characteristics influence police behavior. These findings largely reflect those of suspect characteristics.

Neighborhood Characteristics and Policing Outcomes

Compared to police discretion, much less is known and understood about the ways that neighborhood context shapes police perceptions and behaviors, a hole in the literature lamented by researchers (Klinger 1997; Klinger 2004; Kochel, Wilson, and Mastrofski 2011; Ferrandino 2014). Despite an early analysis of this very topic (Smith 1986), little research has been conducted in the intervening decades to corroborate or build upon the initial findings (Ferrandino 2014). Smith's (1986) study provided evidence that the racial makeup of neighborhoods does affect how police conduct themselves when interacting with civilians. He found disparate outcomes for Black individuals based on the type of neighborhood in which they were stopped, and he proposed that this effect may be due to officers gauging a person's character based on the "type of people" of who live in a particular area. Expanding this argument to a space-based analysis, it is likely that police officers judge people based on the "type of neighborhood" in which they live.

Klinger (1997), employing an ecological model, acknowledged that policing differs across geographic spaces, but he was only able to provide a theoretical

explanation as to why police behavior differed depending on the neighborhood crime rate. More recently, researchers have begun investigating these questions again, and their work has provided insight into the neighborhood characteristics that matter in determining police behavior. For example, structural disadvantage and population mobility have been shown to predict variations in police misconduct across neighborhoods (Kane 2002). Interestingly, police are more likely to "downgrade" their handling of crime and disorder incidents in wealthier neighborhoods, compared to those that are less well off (Lum 2011). These findings indicate that neighborhood characteristics do, in fact, influence how police officers conduct themselves.

In this study, the primary independent variables of interest are the racial and ethnic compositions of neighborhoods. This is, perhaps, the area of neighborhood-level policing research that is most compelling. Importantly, characteristics of a neighborhood are essential in determining how officers perceive its residents, regardless of their ethnic or racial background (Reck 2014). In other words, two neighborhoods that are both predominantly Black may be viewed very differently by police, depending on other factors, such as how well kept the neighborhood is. However, a qualitative analysis revealed that Black communities are especially likely to be considered morally deficient (Vera Sanchez and Rosenbaum 2011), which police officers and agencies may use to justify the need for vigilant policing. Additionally, comparisons between racial and ethnic groups who live near each other play a role in determining how a given group is viewed (Vera Sanchez and Rosenbaum 2011; Reck 2014).

Rather than analyzing static patterns of racial composition, some researchers have instead looked at how population changes affect policing practices. While increases in

percent Latino were related to rises in police misconduct, the same relationship was not detected when the size of the Black population in a neighborhood increased (Kane 2002). The author hypothesized that absence of an effect for the latter group may have been related to the increasing residential concentration of Black residents during the study period. In areas where there are large immigrant Latino populations, police officers note that language barriers inhibit in their ability to effectively interact with the citizens (Culver 2004). Although this does not in itself evince racial disparities of any kind, one can imagine that would be the long-term result.

In line with this study, researchers have also looked at how suspicion of suspects change depending on the racial and ethnic composition of a neighborhood. An observational study examining the formation and emergence of police suspicion discovered that most instances of suspicion occurred in predominantly Black areas (Dunham, Alpert, Stroshine, and Bennett 2005). It is difficult to determine if this effect arises because police are more suspicious in Black neighborhoods, or because officers spend more time in high-crime areas, which tend to be predominantly non-white (Renaur 2012). Either way, the result is that suspicion is associated to a greater extent with Black communities. Neighborhood context also influences police-citizen interactions through the "out-of-place" stop. Researchers have identified this as a common theme, with both white and Black individuals raising suspicion of police officers simply because they appear racially out of place (Dunham et al 2005; Renaur 2012; Rojek, Rosenfeld, and Decker 2012).

Sociological studies of neighborhoods beyond the purview of policing also serve to enhance our understanding of how community context may shape the way an officer

regards a potential suspect. For example, research indicates that perceived disorder in a neighborhood is positively related to the relative size of the Black population, even when controlling for actual crime rates (Sampson and Raudenbush 2004). Similarly, other findings reveal that the level of perceived crime within a neighborhood is positively related to the percentage of the population that are young Black men, even when controlling for actual crime rates and neighborhood economic conditions (Quillian and Pager 2001). Furthermore, perceived, as opposed to actual, racial composition may be an even stronger indicator of perceived victimization risk among Whites (Pickett, Chiricos, Golden, and Gertz 2012). Interestingly, larger Black populations appear to incite fear of crime among white and Black individuals alike (Brunton-Smith and Sturgis 2011). These findings are meaningful to the extent that disorder and Black communities are associated with criminality, and how this influences an officer's interpretation of a suspect's behavior, appearance, or demeanor. Additionally, the belief that certain groups are prone to crime influences where police officers are deployed and the techniques used in across police beats. These are issues I discuss further in the next section.

Although the literature on how neighborhood characteristics influence police behavior is limited, researchers have demonstrated compelling evidence that officers do in fact conduct their jobs differently depending on the setting that they are in. Among the population more generally, the racial composition of a neighborhood, especially the proportion of the population that is Black, affects police officers' perceptions of safety and crime. Surely police officers as a group are not exempt from these cognitive associations. To this point, researchers have left unexamined the mediating mechanisms that connect differences in neighborhood characteristics to differences in stop and frisk

outcomes. Furthermore, given the explicit permission from the Supreme Court to draw on neighborhood traits in order to justify stop and frisks, it is important to consider patterns associated with ecological characteristics as possible evidence of organizational policy. In the next section, I will move to a discussion of how racial and ethnic minority groups, and the spaces in which they reside, have been criminalized vis-a-vis targeted policing.

Criminalization of Race and Space

Another body of sociological literature has illuminated the consequential role that race and ethnicity play in determining the development and application of criminal justice mechanisms (Murawaka and Beckett 2010; Lynch 2011; Van Cleve and Mayes 2015). Motivation for this research grows from the glaring contrast between the ostensibly colorblind laws and policies that constitute our criminal justice system and the persistent overrepresentation of nonwhite individuals, especially Blacks, within that system (Beckett, Nyrop, Pfingst and Bowen 2005; Beckett, Nyrop and Pfingst 2006; Stuart 2011). According to these scholars, this discrepancy should not be viewed simply as a summation of prejudice resulting from individual incidents of discrimination by criminal justice actors. Rather, race and criminality engage in a circuitous and tautological exchange, where each is used to define the other (Eberhardt, et al. 2004; Van Cleve and Mayes 2015). Although policies may make no explicit reference to race or ethnicity, they are formulated in such a way as to implicate people of certain races and ethnicities. There is also a spatial element of this relationship. Not only are the behaviors associated with nonwhite people labeled most menacing to society, but the areas in which they reside are deemed the most dangerous, even when evidence does not bear out such conclusions (Lynch, Omori, Roussell, and Valasik 2013). In this study, the finding that nonbehavioral

stops are more common in minority neighborhoods would provide evidence that the criminality of Blacks and Latinos is perceived differently than for whites.

At the level of policing, a ramification of this syllogism is an imbalanced surveillance and broader informal policing of racial and ethnic minorities and the neighborhoods where they live (Stuart 2011). This discrepancy in the amount of enforcement that occurs across communities has real implications, arising from proactive policing's dependence on seeking out potential crime. Police departments will necessarily find more crime in neighborhoods where they actively look for it. Consequently, by concentrating their forces in minority neighborhoods, they serve to further strengthen the already strong association between people of color, their neighborhoods, and crime. Furthermore, as discussed in the previous sections of the literature review, police treat people of color more harshly than they do White individuals. The process of criminalization described here serves to vindicate that harsher treatment. This association between crime and people of color is especially troubling because it exists within a system that is, allegedly, color-blind. The geographic concentration of policing is further compounded by policing policies that, although at face value, void of any explicit racial or ethnic intent, can have detrimental effects for communities of color (Beckett, Nyrop, and Pfingst 2006). For example, Lynch (2011) describes how the decision of one urban police department to focus on the enforcement of a particular drug, crack cocaine, had a disproportionately negative impact on Black and Latino individuals and communities. Disparities resulting from color-blind policies may be especially difficult to pinpoint, which is one reason why analyses that examine how law enforcement is related to race, ethnicity, and space is so critical at this time.

Although the guardedness of the NYPD makes it difficult for outsiders to examine its guiding organizational ethos (Roy 2009; Eterno and Silverman 2012), there are indicators that the agency engages in practices that encourage the criminalization and mistreatment of minority communities. One such example is Operation Impact, a program launched in 2003 to address the "isolated stubborn pockets [of crime] across the city" (New York City 2010) by flooding those areas with large numbers of police officers. By focusing not only on high-crime areas, but also gangs and public housing, they NYPD is vastly increasing its ability to monitor the behavior and activity of minority individuals. Furthermore, Operation Impact has been used as training ground for newly minted officers straight out of the police academy. This means the officers patrolling the highest-crime neighborhoods in the city are those with the least experience, thus allowing ample room for mistakes to be made and situations mishandled. Again, it is important to note that Operation Impact is, officially, a race neutral policy. Although the stated intent is not to target minority communities, because of how the goals are formulated, that is the resulting effect.

As this collection of studies suggests, sociologists and criminologists have thoroughly documented the inequalities that pervade our criminal justice system, especially the disparate and more severe outcomes for Black and Latino individuals. However, despite acknowledging in a vague theoretical manner the systemic disadvantage experienced by these communities, empirical research on criminal justice inequalities has predominantly been conducted within the same color-blind framework that perpetuates them in the real world (Van Cleve and Mayes 2015). Of particular significance here is that the literature on policing outcomes has focused primarily on how

suspect characteristics influence officer discretion, without accounting for the effects of neighborhood characteristics on policing outcomes. Furthermore, policing research often fails to acknowledge that the policies guiding the day-to-day work of officers are not racially ambiguous in their formulation. In the following section, I will discuss the contributions of this study and introduce the hypotheses that will be tested.

This Analysis

a. Contributions

This study is contributing to the extant literature on policing in a few different ways. First, as discussed above, the preponderance of research on policing analyzes individual incidents and focuses on how suspect characteristics influence police discretion. While this research has revealed the salience of race and ethnicity in policing, it does not address the larger social processes at work. By analyzing dependent and independent variables at the neighborhood level, I am able to provide more insight into these macro-level processes. On a related point, researchers have pointed out the absence of sufficient research on how neighborhood characteristics affect policing. In this study, I explicitly test how neighborhood characteristics influence aggregate police decision making.

The second major contribution of this study is the outcome variable being assessed, namely the reasons that officers provide for stopping suspects. To my knowledge, there is only one other publication to date (Fagan and Geller 2015) that examines this decisionmaking process. Studies of stop and frisk usually measure the occurrence of stops or outcomes subsequent to the stop, such as a frisk, finding of paraphernalia, or arrest. In this case, my interest lies more in the formation of suspicion, a

process that precedes the stop altogether. Furthermore, the categorization of behavioral and nonbehavioral stops has not previously been applied to these data. This categorical scheme will allow me to get at the question of whether and how perceptions of criminality differ based on the racial and ethnic group. If nonbehavioral stops are more common in predominantly Black or Latino, as opposed to White, neighborhoods, that would suggest that neighborhood racial composition makes officers more suspicious of people's appearances.

Finally, most studies of stop and frisk policing at the neighborhood level in New York City that have been conducted so far by doing analyses using larger units of analysis, usually police precincts. Given the large geographic size and high population density of police precincts in New York City, it is easily arguable that they do not represent neighborhoods in any meaningful sense. By using census tracts as my unit of analysis, I am better equipped to detect neighborhood-level differences in stop patterns.

b. *Hypotheses*

Based on the literature described in this chapter, I propose the following hypotheses that are tested in the subsequent analyses:

Hypothesis 1: The rate of nonbehavioral stops in a neighborhood will increase as the proportions of Black or Latino residents increases.

Hypothesis 2: The proportion of nonbehavioral stops will increase as the proportion of Black or Latino residents increases.

Hypothesis 3: The effect that the proportion of Black or Latino residents has on the proportion of nonbehavioral stops will be moderated by the perceived crime rate in a neighborhood.

Hypothesis 4: The proportion of nonbehavioral stops that are "successful" will decrease as the proportion of Black or Latino residents increases.

Chapter Summary

In this chapter, I reviewed the extant literature on policing, divided into three categories. The first group consisted of studies that analyze how suspect characteristics influence police officer discretion. Together, these studies revealed that Black and Latino individuals tend to fare worse in encounters with police than do their white counterparts. The next group consisted of studies that assess the effects of neighborhood characteristics on community policing outcomes. Mirroring the results of individual-level studies, these results suggest that minority neighborhoods are considered more dangerous and criminal than predominantly white areas. The third category of literature explicitly portrays these disparities as non-accidental consequences of policies that, while apparently color-blind, are formulated so as to differentially and negatively affect communities of color. Furthermore, minority racial and ethnic status and criminality are intertwined in a recursive relationship, in which each is drawn upon to define the other. Finally, contributions of this study and hypotheses were reviewed. In the next chapter I discuss the research methods used to conduct this study.

Chapter 4: Research Methods

In this chapter I provide an overview of the methods used in conducting this study. First, I will describe the three data sources and how they are integrated in order to address the hypotheses described above. Second, I report how each of the relevant concepts is operationalized and measured within my models. Finally, concluding this chapter is a discussion of the analytic strategy I use to test my hypotheses, progressing from summary statistics and exploratory spatial analyses through a series of OLS regression models. In this section I also explain how the strategy employed in this study expands upon and adds to the extant body of literature exploring patterns in stop and frisk policing in New York City.

Data Sources

a. NYPD Stop, Question, and Frisk Database

Subsequent to class-action lawsuits brought against the NYPD *(Daniels, et al. v. the City of New York* 2001; *Floyd v. the City of New York* 2013) regarding the racially disparate outcomes of stop and frisk, the Department has been under court mandate to make data resulting from the policy readily available to the public. In the mid-2000s, they began doing so through their online stop, question, and frisk database, which provides data files containing information about all recorded stops. The database currently provides stop data for the years 2003 to 2014.

The information provided in this database is culled from the UF-250, a form that police officers must fill out and submit to a precinct supervisor, subsequent to conducting a stop that meets certain criteria. NYPD policy requires officers to document them on a UF-250 if the suspect is: 1. stopped using a verbal authoritative command (verbal use of

force), 2. frisked or searched, 3. arrested, or 4. stopped and then refuses to identify him or herself. Although there was no legal regulation mandating that NYPD officers record stop-and-frisk encounters prior to the settlement in *Daniels vs. the City of New York* (U.S. Commission on Civil Rights 2000), this policy has been in place since the mid-1980s. Additionally, documenting stop and frisks has been an official organizational priority since 1997, in part to protect police officers and the department from allegations of police misconduct (Spitzer 1999).[2] This analysis is conducted using approximately 4.5 million observations from the database between the years 2003 and 2014.

The UF-250 describes characteristics of both the suspect and the stop. The suspect characteristics include race and ethnicity, age, and sex, as well as other physical identifiers. The officer is also asked to report when the stop took place, why the suspect was stopped, if a frisk ensued and whether any drugs or weapons were discovered therein, occurrences of officer use of force, and whether further punishment was warranted (i.e. a summons or an arrest). Importantly, the location of the stop is also recorded, although the level of detail varies across years. From 2003 to 2005, either the address where the stop occurred or a nearby intersection is provided. For the years 2006 onward, x/y coordinates are supplied for the vast majority of stops, allowing for greater geographic precision. The remaining stops list the address or nearest intersection, as in previous years.[3] ArcGIS software was used to geocode those observations missing x/y

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[2] It is not uncommon for officers to submit UF-250s regarding situations that do not meet these standards. However, well over 50% of recorded stops do meet the criteria listed previously (Coviello and Persico 2013), and conducting analyses using only the subset of stops that require documentation does not affect the relative rates of stops across racial and ethnic groups (Gelman, Fagan and Kiss 2007).

[3] An exception to this pattern exists for the year 2006, in which 2.03% of the cases (n = 10,285) have neither x/y coordinates nor an address. However, the distribution of observations missing location information generally reflects the distribution of stops across precincts. These data points are thus considered missing at random, and not in violation of the assumptions of ordinary least squares regression.

coordinates.[4] However, the unit of analysis in this study is the neighborhood, conceived

of as a census tract. To aggregate the data to an appropriate level, I utilized ArcGIS

software to assign each stop to a census tract, based on its geographic location. The

sample consisted of 2129 census tracts, with a separate observation for each year,

resulting in a final sample size of 25,548 observations.

b. *U.S. Census Bureau American Community Survey Five-Year Estimates (2006-*

   2010)

Census-tract level demographic information is drawn from the American

Community Survey (ACS) 2010 five-year estimates (Minnesota Population Center

2011).[5] These years cover the middle point of the policing data using in analyses. Topics

of interest include race, age, and sex composition, socioeconomic status, educational

achievement, residential instability, and income inequality. The ACS is an ongoing effort

by the United States Census Bureau to collect and report vital information annually in

order to better track population changes occurring between the major data collection

efforts of the decennial census. This survey is conducted nationally each year, in order to

assess social, economic, demographic and housing trends. Using demographic census

data to operationalize neighborhood-level independent and control variables is common

in criminological literature, and follows prior research analyzing stop and frisk patterns in

New York City (Geller and Fagan 2010; Evans, Maragh and Porter 2014; Ferrandino

2015). Variables from the ACS and the stop, question, and frisk database were merged in

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[4] I was able to successfully geocode 53.98% (n = 516,685) of these observations. The final sample included
91% (n = 4,578,167) of all stops recorded.
[5] These figures are calculated by pooling annual samples from years 2006 through 2010, and then providing
appropriate weights to produce population estimates.

order to construct a comprehensive dataset, containing demographic and stop-and-frisk measures for each census tract in New York City.

c. New York City Crime Data

Neighborhood crime rates were estimated using precinct-level measures. Precinct-level crime data come from the NYPD (Historical New York City Crime Data 2015). Each census tract was assigned a police precinct by using ArcGIS software to determine which precinct boundary it falls within, and was then allocated the appropriate crime measures.[6,7] The NYPD provides crime counts, which I used to calculate rates based on the population size, as described in the next section.

To conduct these analyses, these three data sources were integration into a single census tract-level dataset. The dataset covers all neighborhoods in New York City, and includes measures of stop and frisk activity, demographic and economic characteristics, and reported crime levels. In the next section, I will explain how the central concepts of this analysis are operationalized using data from the sources described here.

Operationalization and Measurement of Variables

In this study, I address the question of how contextual factors influence police decision making before and during a stop and frisk encounter with a suspect. Specifically, each of my research questions is aimed at exploring how neighborhood traits predict the rates of non-behavioral stops at the neighborhood level. While previous research has

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[6] In most cases census tract and precinct boundaries align with one another. A major exception is census tract 228 in Staten Island, which is evenly split between precincts 122 and 123; it was ultimately assigned to the latter. Because the racial compositions of the precincts in question are similar, and the total number of stops in the census tract over the twelve-year study period is only 665, this decision is not expected to have any meaningful effect on the results.

[7] It should also be noted that the 121st precinct on Staten Island was instituted in July of 2013. This precinct encompasses an area that previously fell under the purview of either the 120th or 122nd precincts. For this reason, some census tracts in Staten Island have a different precinct designation in 2014 compared to earlier years.

focused almost exclusively on the occurrence of stops and the subsequent outcomes, such as frisks, arrests, and use of force (Fagan, Geller, Davies and West 2009; Geller and Fagan 2010; Ferrandino 2014), one of the primary features of interest in this study is the decision-making process that occurs prior to the initiation of a stop and how neighborhood characteristics influence that process.

To capture this process, I analyze the reasons that police officers self-report for stopping individual suspects, categorizing them as either 'behavioral' (based on the suspect's actions/behavior) or 'nonbehavioral' (based on the suspect's appearance). This categorical scheme is drawn from a series of previous observational studies conducted by Alpert, Dunham, and colleagues (Alpert, Dunham, Stroshine, Bennett and MacDonald 2004; Alpert, MacDonald and Dunham 2005; Dunham, Alpert, Stroshine and Bennett 2005), during which researchers participated in ride-alongs with on-duty police officers in Savannah, Georgia. These studies concluded that nonbehavioral stops are more likely to occur in predominantly black neighborhoods. Accordingly, the primary independent variable of interest here is the racial and ethnic composition of the neighborhood. Finally, other neighborhood-level characteristics are integrated into my models as control variables. Summary statistics for all variables are presented in Table 1.

a. *Dependent Variables*

This analysis has three dependent variables. The first research question addresses the rate of nonbehavioral stops, while the second two research questions examine the proportion of non-behavioral stops. The nonbehavioral stop rate is based on the number of nonbehavioral stops that occur divided by the population size of the census tract. The proportion of nonbehavioral stops is calculated by dividing the number of nonbehavioral

stops in a census tract by the total number of stops in that tract. The measurement of nonbehavioral stops is based on an item from the UF-250 form, which asks officers to provide a reason for initiating a stop. The form consists of ten check boxes, which, it has been argued, were specifically designed to meet the standards of reasonable suspicion (Fagan and Geller 2015). The reporting officer may check off as many of these explanations as he or she likes.

The following reasons are considered non-behavioral: fits a relevant description, wearing clothes commonly used in a crime, and suspicious bulge. Behavioral explanations for a stop include carrying a suspicious object, casing a victim or location, acting as a lookout, actions of engaging in a violent crime, actions indicative of a drug transaction, and furtive movements. The tenth and final explanation is 'other.' For the purposes of this analysis, it is important to ensure, as best as possible, that any detected relationships are based on the nuanced distinctions between behavioral and non-behavioral stops. Accordingly, the label of non-behavioral is uniquely applied to stops in which only non-behavioral reasons are provided. In other words, if a stop is coded as having been conducted because a suspect fit a relevant description *and* was casing a victim or location, it is not considered to fall into the category of nonbehavioral. Overall, 17% of stops fall into the category of nonbehavioral (see table 1). The number of nonbehavioral stops ranges from 0 to 1665 per year, with the average number being 23.

The third research question requires a different outcome measure. In this case the rate of "successful" non-behavioral stops within a neighborhood is the outcome of interest. In the final models, I separately analyze behavioral and non-behavioral stops, and I examine how neighborhood characteristics predict the "success" rates of stops

falling into each of these categories at the census tract level. Although the "success" of a stop may be measured in a variety of ways, for the purpose of this analysis a stop will be considered "successful" if an arrest is made. Other studies have measured success based on whether marijuana (Geller and Fagan 2010), pistols (Ferrandino 2013), or contraband (Gumbhir 2007) were found on the suspect. Because an arrest is often made subsequent to finding guns or drugs, as well as under many other circumstances, arrest may be considered a measure of "success."[8] It is noteworthy that an arrest results from only 6% of stops, which is a strong indication that, in practice, either the requirements to meet reasonable suspicion do not nearly approximate those of probable cause or are simply not being met at all. The average proportion of nonbehavioral and behavioral stops that are "successful" are .10 and .07, respectively. Comparing the "success" rates of behavioral and nonbehavioral stops provides an opportunity to examine if suspicions based on appearance alone are more or less accurate than those based on behavior.

b. *Independent Variables*

The primary independent variable of interest is the racial and ethnic compositions of neighborhoods. As described in the literature review, prior research has demonstrated that neighborhood racial composition, most notably the proportion of the population that is Black, is a significant predictor of the occurrence of stops. A focal purpose of this study is to gain a better understanding of how the racial and ethnic characteristics of a neighborhood influence the decisions of police officers. Census tract population counts by race and ethnicity from the 2010 census are used to determine the proportion of

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[8] In the dataset, there were only 1,006 instances in which a gun was found but no arrest was made, compared to a total of 300,229 arrests. Therefore, the results of this analysis would likely not change by including the former group as "successful" stops.

residents belonging to each of the following groups: White, Black, Latino, Asian, and other. Each proportion will be calculated by dividing the number of residents who belong to that racial or ethnic group by the total census tract population. The percentage white is left out of the model in order to avoid multicollinearity among the variables.

Table 1: Descriptive Statistics of Dependent and Independent Variables				
	MEAN	S.D.	MIN	MAX
Dependent Variables				
Nonbehavioral Stop Count	23.37	38.28	0	1665
Proportion nonbehavioral stops	0.17	0.13	0	1.00
"Successful" nonbehavioral stops	0.10	0.16	0	1.00
"Successful" behavioral stops	0.07	0.09	0	1.00
Independent Variables				
Population: Black	0.25	0.23	0	0.87
Population: Hispanic	0.27	0.16	0.01	0.66
Population: White	0.33	0.21	0.01	0.99
Population: Asian	0.13	0.10	0	0.47
Population: othe race/ethnicity	0.02	0.02	0	0.15
High Crime Designation	0.51	0.17	0	1.00
Control Variables				
Males age 16-24	0.07	0.01	0.03	0.09
Concentrated disadvantage	0.39	0.59	-1.15	1.83
Residential instability	0.35	0.40	-1.12	1.16
Gini coefficient	0.44	0.04	0.35	0.53
Murder rate	0.06	0.08	0	3.32
Burglary rate	2.89	5.32	0.96	220.00

The measures of racial and ethnic composition also demonstrate strong variation across neighborhoods. The proportion of the population that is Black ranges from zero to 0.87, with a mean of 0.25. Similarly, the proportion Latino population is as low as 0.01 in some neighborhoods and as high as 0.66 in others, with a mean of 0.27. The proportion

White population demonstrates a similar wide-ranging pattern. Given the magnitude of the standard deviations, these numbers suggest patterns of racial segregation.

A second concept that is integral to this study is perceived neighborhood crime level. Perceived crime is operationalized using an item from the UF-250. This item, which, like the stop reasons, is a simple checkbox, can be found under the "other circumstances" section of the form. The officer is instructed to select this item if they believe that the area in which the stop occurred is a "high-crime" area. This stop characteristic is aggregated to the neighborhood level by calculating the proportion of stops within a census tract for which this option is selected, such that greater values signify that officers consider a neighborhood to be "crime prone." The value of the variable ranges all the way from zero to one. A value of zero indicates that no officer making a stop considered the neighborhood to be dangerous. A value of one, on the other hand, means that the neighborhood was considered dangerous in all stop instances. On average, 51% of stops are designated as occurring in a high-crime area, with a standard deviation of .17. Although perceived crime is not necessarily an accurate indicator of actual crime rates, other studies of police decision making have used this or similar items as the sole measure of crime (Smith 1986; Alpert, et al. 2005; Ferrandino 2014). Because perceptions of crime are racialized, this variable is likely measuring a construct that is distinct from actual crime. The distribution of this variable instead signals that there is a reasonable degree of disagreement, such that half of stops in a neighborhood are considered to occur in a high-crime area, and the other half are not.

c. Control Variables

Based on previous literature, other neighborhood characteristics are controlled for using measures from the ACS. To account for the relative potential for crime, I include the proportion of the population within a neighborhood that are males between the ages of 15 and 24. Because education level may influence individual propensity for crime (Lochner and Moretti 2004), the proportion of the population that has completed at least some college is calculated.

I control for neighborhood socioeconomic status using the following indicators: the proportion of households with an income below the poverty line in the past 12 months; median household income; median home value; proportion of homes with female heads of household; proportion of residents at least 25 years of age who have at least some college education; and proportion of the labor force that is unemployed. Due to typically high levels of multicollinearity among these measures, it is customary in the neighborhoods and crime literature to create an index out of these items in order to capture the concept of concentrated disadvantage (Land, McCall and Cohen 1990; Krivo and Peterson 2000). This index was calculated by summing the standardized z-scores of each measure, and then dividing by five to yield an average. A higher index value signals greater socioeconomic disadvantage.[9] In addition, I include the Gini coefficient for each census tract, which provides an estimation of the level of income inequality within a given area. It has been argued that income inequality may be a better predictor of neighborhood-level crime than measures of poverty alone (Hipp 2007).

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[9] To ensure that these items all reflect the same construct, I completed a factor analysis, which returned a single factor with an eigenvalue greater than 1. This result, along with the calculated Cronbach's alpha value of $\alpha = 0.81$, suggests that all five items are in fact measuring the same phenomenon.

Similarly, an index of residential instability was created using the proportion of owner occupied homes and the proportion of residents who moved to the neighborhood within the past five years. The former measure is included, as homeowners may take better care of their property. This is an important factor, so far as the neighborhood aesthetic influences officers' perceptions of disorder within a neighborhood. The percentage of new residents is a common measure used in neighborhoods and crime literature, as it may influence social cohesiveness among residents and commitment to neighborhood upkeep (Sampson, Raudenbush, and Earls 1997; Nielsen et al. 2005; Krivo, Peterson, and Kuhl 2009).[10] The index was calculated by summing the z-scores of each item and dividing by two to yield an average. Higher values signal greater residential instability.

Reported crime rates are also important for explaining police activity, especially regarding the dispersion of officers throughout the city, and why some communities may have many assigned police and others very few. For reasons described in the previous section, actual crime is measured at the precinct level. Because all official crime statistics have their weaknesses, I include two distinct crime variables: homicide and burglary. The NYPD provides the number of occurrences of each type of crime for each year. To account for annual fluctuations, I averaged these crime counts over the course of the study period. In order to take the size of the population of a neighborhood into question, I calculated crime rates by dividing the average number of occurrences by the precinct population, and multiplying by 1000. This yielded the average annual rate of homicides and burglaries per 1000 residents. The average murder rate is 0.06, and average burglary

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[10] Factor analysis was conducted on these two variables, returning a single eigenvalue greater than 1. The Cronbach's alpha value for this concept is α= 0.77.

rate is 2.89. Homicide is considered a reliable measure of crime, due to the fact that it does not go unreported as frequently as other serious crimes, and is often used as an estimate of neighborhood crime (Sampson, Raudenbush, and Earls 1997). However, it is also an exceedly rare crime, and there are many instances where precincts experience no homicides over the course of a year or more. Because of this, I also calculate the rate of burglaries per 1000 residents. Although burglary does suffer from underreporting, comparisons between official crime reports and victim surveys reveal that burglary has a high degree of convergence compared to other index crimes (O'Brien, Shichor, and Decker 1980; Ansari and He 2015).

Finally, dummy variables to control for year and precinct will be included in each model. This allows for the ability to control for changes over time, which is especially important given changes in the implementation of stop and frisk since the 2013 ruling. Including an indicator of the police precinct will help to address differentiation in organizational practices across smaller units of command.

Analytic Strategy

In this section I describe the analyses used to address my research questions, and why they are appropriate for this study. In order to assess the basic relationships between variables, the investigation begins with a review of the correlation matrix displaying coefficients for bivariate relationships among all variables. From there, I explore spatial patterns among the dependent variable and then explicitly test each hypothesis. The existence of spatial patterning is examined by running Moran's I and the LISA statistic. I then provide a brief overview of the problem of spatial autocorrelation, and how it is

addressed in this study. Finally, I estimate a series of regression models to specifically test each hypothesis.

a. *Exploratory Spatial Analysis*

As discussed in the literature review, the element of physical space is central to urban policing practices. Based on a variety of characteristics--if a neighborhood is commercial or residential, who occupies it, if it is perceived as dangerous, or other factors--the presence of police varies greatly across a city's landscape, as do the relationships between the police and the people whose behavior they monitor. While it is common in the neighborhoods and crime literature to analyze the relationships between neighborhood characteristics and crime or law enforcement patterns, it is more unusual to examine these patterns across space. Furthermore, studies that have performed spatial analysis of NYPD stop and frisk practices usually focus on the distribution of stops or stop outcomes across the city (Gelman, Fagan and Kiss 2007; Geller and Fagan 2010; Evans, Maragh and Porter 2014). In contrast, the spatial analysis conducted in this study will concentrate on the reasons that police officers provide for stopping suspects, specifically whether designating stops as nonbehavioral is a spatially clustered phenomenon. I will begin the exploratory portion of this study by mapping out the distributions of key variables of interest, and summarily comparing them.

I use the spatial statistic known as Moran's I in order to see if nonbehavioral stops are spatially clustered at the census tract level. While social scientists are often concerned with clustering, Moran's I is a general measure of spatial distribution, and it can also be used to detect spatial dispersion. The computational process involves comparing a characteristic of interest of a geographic unit, in this case a census tract, with that of each

of its neighbors; the difference between these values is then compared to the difference in

values between all geographic units included in the analylsis (Mitchell 2009). Once this

procedure has been completed for each feature, a single i-value is generated for the whole

dataset, indicating if either spatial clustering or dispersion is present. This value ranges

from -1 to 1. A value of -1 signifies complete dispersion, or that the units of interest are

as spread out as possible. A value of 1 signifies complete clustering. A value of zero

signals a spatially random distribution.

If spatial clustering is detected, the next step is to calculate the Anselin Local

Moran's I, also known as the LISA statistic. Whereas the global Moran's I, introduced

above, determines the presence of statistically significant spatial patterns, the local

Moran's I identifies "hot spots" of values of interest (Anselin 1995). In the context of this

study, the LISA statistic indicates *where* in New York City nonbehavioral stops are

unusually prevalent. This measure is considered to be local because it compares a

characteristic of a target feature only against those of its neighbors. A positive value

signals that a census tract is surrounded by others with similar values for the

characteristic in question. If the relationship is statistically significant, this translates into

spatial clustering. A negative value suggests that the census tract is surrounded by others

that are not similar. Statistical significance in this case is suggestive of a spatial outlier.

By estimating the Moran's I and LISA statistics, I am able to determine if high

proportions of nonbehavioral stops are spatially clustered at the neighborhood level.

Evidence of spatial clustering would be noteworthy, as it may suggest that nonbehavioral

stops are spatially dependent on other neighborhood characteristics. Furthermore,

visualizing on a map the distribution of neighborhood characteristics, as well as the

results of the LISA analysis, assists in untangling the underlying relationships between the dependent and independent variables. Following this exploratory spatial analysis, I then continue on to traditional OLS regression, accounting for spatial dependence.

b. *Accounting for Spatial Dependence: The Egohoods Approach*

In any type of research that examines patterns across space, the consequences of spatial autocorrelation are a concern. Spatial autocorrelation refers to the tendency for "things near each other [to be] more alike than things far apart" (Mitchell 2009, 104). For example, if a census tract is surrounded by other census tracts that have high crime rates, we would expect the census tract in question to also have a high crime rate. Analytically, the presence of spatial dependence means that the characteristics of any unit must be analyzed within the context of its neighboring units, rather than in isolation. Traditional regression techniques, including OLS, do not take into account the effects of spatial autocorrelation. Therefore, accounting for these effects is essential for estimating of crime across space (Andresen 2011; Light and Harris 2012). Although the dependent variable in this analysis is a measure of police decision making, rather than of crime, it is assumed that the same concerns exist.

In order to account for spatial dependence in my models, I incorporate the concept of egohoods, which provides a novel way to construct neighborhoods (Hipp and Boessen 2013). Rather than conceiving of neighborhoods as constricted by what are often arbitrary boundaries, such as census tracts, egohoods are developed with the understanding that neighborhoods overlap with one another. Consequently, egohoods are constructed by drawing a buffer, of some set distance, around the center point of each unit of analysis. An egohoods code, developed for the statistical software package Stata,

then goes through each unit of analysis and measures the mean value of each variable for its unique egohood. In this way, each unit is assigned values that inherently take into consideration those of its neighbors. For this study, egohoods were developed using a buffer of two miles around each census tract, and egohood values were calculated for all dependent and independent variables drawn from the ACS. This differs from traditional spatial lag models, which including both the original variable and a separate lagged variable that compensates for spatial dependence.

    c. Count Model of Nonbehavioral Stops

Because the primary independent variable of interest in this study is the racial and ethnic compositions of neighborhoods, it is important to first establish that minority neighborhoods are, in fact, inequitably policed. Model 1 regresses neighborhood-level stop rates on racial and ethnic composition and other neighborhood characteristics in order to establish that nonbehavioral stops occur more frequently as the proportion of Black and Latino residents increases (hypothesis 1). A negative binomial regression model is employed to address overdispersion in the data (Long and Freese 2014). The census tract population will be used as an exposure term in this model, so that the outcome will be a stop rate per population.

    d. Regression of Nonbehavioral Stops on Neighborhood Characteristics

Ordinary least squares regression is used to test hypotheses 2 and 3, regarding the influence that neighborhood characteristics, notably racial composition and the perceived crime rate, have on the proportion of non-behavioral stops. Hypothesis 2 predicts that the proportion of nonbehavioral stops will increase as the proportion of Black or Latino residents increases. To assess the underlying relationship between racial composition and

nonbehavioral stops, model 2 regresses the proportion of nonbehavioral stops only on the racial and ethnic composition variables. Model 3 adds the control variables so as to test whether racial and ethnic composition remain a significant predictor of nonbehavioral stops when accounting for other neighborhood characteristics.

The perceived crime rate in a neighborhood is another variable that is worthy of additional scrutiny. If an officer believes that he or she is patrolling a high-crime area, he or she may consequently interpret a suspect's behavior differently. Prior research has demonstrated that suspect race and ethnicity become weaker predictors of police behavior when taking other, seemingly race-neutral contextual factors into consideration (Tillyer 2013). Because perceptions of crime are racialized, it is reasonable to predict that the effect of racial composition will be partially moderated by the perception of the dangerousness of the neighborhood. Model 4 introduces the perceived high crime variable, to assess its role in predicting the proportion of nonbehavioral stops. Then, to test this idea hypothesis 2, model 5 introduces interaction terms between the high crime measure and both the proportions of Black and Latino residents. Conceptually, incorporating an interaction term allows me to test if the magnitude of the relationship between the proportions of Black and Latino residents and nonbehavioral stops is dependent on the perception of a neighborhood as a high- or low-crime area (Aiken and West 1991). A significant result would signify that racial and ethnic composition and perceived high-crime rates are characteristics that should be analyzed in tandem with one another when predicting variation in police behavior.

In order for OLS to produce valid coefficient estimates, the variables must meet certain regression assumptions. Two of the most important of these assumptions pertain

to heteroscedasticity and multi-collinearity. Heteroscedasticity occurs when variation in the dependent variable differs across values of the independent variables. Although heteroscedasticity does not result in biased coefficient estimates, it is problematic because it leads to inefficiency and biased standard errors (Allison 1999). To test for heteroscedasticity in the present analysis, I ran the Breusch-Pagan test after regressing the outcome measure on all of the independent variables. The results suggest that heteroscedasticity is present. In order to diminish any bias in the estimates, I used robust standard errors in each OLS model. I also tested for multicollinearity by running variance inflation factors (VIFs) among all of the variables. All of the resuling VIFs had values less than 7, indicating that there is no problematic multicollinearity (Acock 2012).

    e. Regression of "Success" Rates on Neighborhood Characteristics

       The final two models address hypothesis 4, regarding the "success" rates of nonbehavioral stops. As discussed in the literature review, "success" rates of stops are lower for minority individuals, a finding which holds even as the definition of a "successful" stop changes (Gumbhir 2003; Ferrandino 2013; Geller and Fagan 2010). Applying this relationship to the neighborhood level, I predict that the proportion of "successful" stops will decrease as the proportion of Black residents increases. Accordingly, model 6 regresses the dependent variable of proportion "successful" nonbehavioral stops on the racial and ethnic population variables, as well as the other neighborhood-level control variables included in the previous models. To serve as a comparison, I will run a model that predicts "successful" behavioral stops, but is otherwise identical (model 7) in its components.

In the present chapter, I introduced the methods used to conduct these analyses. I began by describing each of the three data sources, which provide information about stops in New York City, neighborhood level demographic measures, and crime statistics. These sources are integrated in order to provide a comprehensive picture of how neighborhoods vary across the city's landscape. I then explained how the dependent, independent, and control variables are being operationalized. I then described the exploratory spatial analyses that will be executed in order to gain a stronger understanding of how stop reasons vary across space. Finally, I discussed the problem of spatial autocorrelation and how it will be addressed, and summarized the statistical models that will be used to test my hypotheses. The next chapter will reveal the results of each of the analyses described here.

Chapter 5: Results

In this chapter, I present the analyses described previously and report the findings. I begin by reviewing the bivariate correlation coefficients to establish the baseline relationships between the dependent, independent, and control variables. With a basic understanding of the distribution of the data in hand, I then move to the exploratory spatial analysis and present the findings of the Moran's I and LISA analyses. I then progress to the main analyses of this study, starting with a count model of nonbehavioral stops per population (hypothesis 1) and proceeding through a series of regression models, with corrections for spatial autocorrelation, predicting the percentage of nonbehavioral stops (hypotheses 2 and 3). In the final section, models predicting the percentage of "successful" behavioral and nonbehavioral stops are presented (hypothesis 4).

Bivariate Relationships

The correlation matrix shown in table 2 portrays the bivariate relationships between the proportion of nonbehavioral stops, crime measures, and demographic characteristics. Contrary to my expectations, nonbehavioral stops are negatively correlated with the Black population when not accounting for the influence of other neighborhood characteristics. In contrast, the relationship between nonbehavioral stops and the proportion Latino population is positive. The opposing directions of these relationships suggest that processes of policing differ between Black and Latino neighborhoods. The variable most strongly correlated with nonbehavioral stops is perceived high crime crime, to which it is negatively related. One explanation for this relationship is that as police perceive the level of danger to increase, they are more likely

47

Table 2: Bivariate Statistics

	Proportion Nonbehavioral Stops	Proportion White Population	Proportion Black Population	Proportion Latino Population	Proportion Asian Population	Proportion Other Population	Proportion Stops Designated "High Crime"	Proportion Young Males	Concentrated Disadvantage Index	Residential Instability Index	Gini Coefficient of Income Inequality	Murder Rate/1000 Residents	Burglary Rate/1000 Residents
Proportion Nonbehavioral Stops	1.00												
Proportion White Pop	0.01	1.00											
Proportion Black Pop	-0.04	-0.71	1.00										
Proportion Latino Pop	0.09	-0.52	-0.10	1.00									
Proportion Asian Pop	-0.07	0.33	-0.60	-0.26	1.00								
Proportion Other Pop	-0.03	-0.29	0.15	-0.07	0.20	1.00							
Proportion High Crime Stops	-0.39	-0.11	0.12	-0.07	0.06	0.09	1.00						
Proportion Young Males	0.00	-0.74	0.49	0.55	-0.42	0.10	0.07	1.00					
Concentrated Disadvantage	0.05	-0.74	0.41	0.71	-0.45	-0.08	-0.01	0.84	1.00				
Residential Instability	0.10	-0.14	-0.15	0.55	-0.21	-0.19	-0.13	0.06	0.33	1.00			
Gini Coefficient	0.07	0.26	-0.22	0.12	-0.20	-0.26	-0.16	-0.23	-0.04	0.76	1.00		
Murder Rate/1000 Residents	-0.01	-0.39	0.43	0.12	-0.34	0.07	0.05	0.32	0.37	0.12	0.05	1.00	
Burglary Rate/1000 Residents	0.01	0.00	0.03	-0.02	-0.04	0.04	0.00	-0.05	-0.03	0.08	0.10	0.32	1.00

to discern suspects' behaviors as criminal. If this is the case, there would be fewer stops based on appearance alone. The proportion of nonbehavioral stops is positively related to the measures of concentrated disadvantage, residential instability, and the Gini coefficient. There appears to be no relationships between the proportion of nonbehavioral stops and the young, male population of a neighborhood.

Interestingly, the relationship between perceived crime and actual crime is virtually nonexistant. Perceived crime has correlation coefficients of just 0.05 and 0.00 with its relationships to the murder and burglary rates, respectively. One possible explanation for this weak association is that the crime rates are drawn from precinct-level data, and may thus not reflect census-tract level crime rates very accurately. Also noteworthy is that perceived crime is related to proportion Black and proportion Latino residents in opposing directions. While the perception of a neighborhood as high-crime increases along with the Black population, officers actually perceive neighborhoods with larger Latino populations as having less crime.

The bivariate relationships between the Gini coefficient of income inequality and the race and ethnic categories suggests patterns of residential segregation may matter for stops, given the spatially oriented nature of policing. Income inequality increases as the proportion White population increases, indicating that Whites are more likely to live in economically diverse neighborhoods. In contrast, income inequality decreases as the proportion Black population increases. Because the proportion Black population has a strong positive relationship with concentrated disadvantage, this suggests not only that Blacks live in less economically diverse areas, but that these areas are more likely to be poor. Like Whites, the Latino population is positively related to income inequality. These

fundamental relationships are important, insofar as poverty makes residents easy targets for police misconduct.

In this section I reviewed the distribution of theoretically significant variables and their bivariate relationships with one another. In doing so, I demonstrated evidence of residential segregation defined by race and socioeconomic status, issues that may have important implications for patterns of policing, as well as the decision making processes of officers on patrol. Notably, I also found preliminary evidence that contradicts the relationship I predicted between racial composition and nonbehavioral stops. Specifically, when not controlling for other neighborhood characteristics, the proportion of the population that is Black is negatively correlated with the proportion of nonbehavioral stops. The next section will proceed with exploratory analysis by examining the spatial patterns of nonbehavioral stops and other neighborhood characteristics that have been established as empirically important when analyzing patterns of policing and officer behavior.

Exploratory Spatial Analysis

a. Distributions of Relevant Neighborhood Characteristics

As discussed in the literature review, space is a concept of paramount concern in the study of policing. Just as neighborhoods consist of people, they also consist of physical space. The residents of a neighborhood and space in which they reside are circuitously employed to define the other, such that people who live in a neighborhood that appears run-down may be deemed disorderly, and neighborhoods composed of individuals perceived of as dangerous, namely poor minorities, may be assumed to foster crime, regardless of the veracity of this assumption (Sampson and Raudenbush 2004). In

this study I examine the extent to which nonbehavioral stops are related to the racial composition of a neighborhood, as well as police perceptions of crime in the area. If my hypotheses are correct, neighborhoods with high proportions of non-behavioral stops will overlap with neighborhoods that have a high proportion of Black and Latino residents and are perceived to be high in crime. Visually representing distributions of important variables across the city may assist in assessing these relationships. All figures can be found in Appendix A at the end of this document.

Figure 1 is a map of all census tracts in New York City, shaded according to the proportion of nonbehavioral stops. According to this figure, nonbehavioral stops are particularly common in the upper Bronx and western Brooklyn, and less so in Queens and most of Staten Island. Figure 2 shows the proportion Black population in each neighborhood. In line with the descriptive statistics and bivariate relationships, the pattern seems to indicate residential segregation. Importantly, the neighborhoods with greater Black populations do not, by and large, overlap with neighborhoods with high proportions of nonbehavioral stops. In fact, with the exception of the upper Bronx, the areas with lower proportions of nonbehavioral stops in Figure 1 have higher Black populations as illustrated in Figure 2, and vice versa. Figure 3 displays the proportion Latino population of each neighborhood. Interestingly, more so than figure 2, the pattern of Latino residence appears to correspond more closely with nonbehavioral stops. Finally, Figure 4 illustrates the neighborhoods designated as high crime. In this case, darkly shaded census-tracts imply that police officers perceive the neighborhood to be dangerous. Perceived high-crime neighborhoods largely mirror predominantly Black

neighborhoods and, similarly, seem to contrast with neighborhoods where there are higher proportions of nonbehavioral stops.

Displaying these variables in map form provides an opportunity to gain a more accurate comprehension of the spatial element of stop and frisk policing. The maps presented thus far summarily suggest that the neighborhood-level policing variables I am analyzing here are not randomly distributed across the city. In other words, the reasons that police officers provide for stopping suspects are tied to the physical location of those stops. By employing spatial statistics, I will be able to verify if there are, in fact, statistically significant spatial patterns of high or low rates of nonbehavioral stops.

b. *Moran's I*

As described in the previous chapter, Moran's I is a statistic that determines whether the distribution of a particular characteristics is randomly distributed across space or, alternatively, if there is a spatial pattern that is statistically different a random distribution. For this study, evidence of spatial clustering of police decision making is important, as it suggests that police conduct their work differently depending on the context. It also emphasizes the need to account for spatial dependence in my regression models. To test for spatial patterning, I ran the Moran's I using a Euclidean distance weight matrix and a distance band of two miles. The resulting statistic had a value of $i =$ 0.39 and a standardized z-value of $z = 110.76$, leading to a spatial relationship of statistical significance ($p < .01$). The positive i value stipulates that there is spatial clustering, rather than spatial dispersion, of the proportion of non-behavioral stops. Therefore, neighborhoods with high proportions of nonbehavioral stops are surrounded by neighborhoods with similarly high values, while neighborhoods with low proportions

of nonbehavioral stops are surrounded by neighborhoods with similarly low values. As explained earlier, Moran's I is a global statistic, which only determines the presence of statistically significant spatial patterning. In order to establish where this patterning is occurring, it is necessary to use the LISA statistic.

   c.   *LISA Statistic*

To determine where the spatial clustering of nonbehavioral stops is occurring, I calculated the LISA statistic for the proportion of nonbehavioral stops for each census tract. The LISA statistic compares the proportion of nonbehavioral stops in a census tract with those around it, in order to assess the similarity in values. In this way, the statistic reflects where high and low values are clustered within the city. The results of this analysis are illustrated in Figure 5. From this figure it is clear that there is very strong spatial patterning at play. In line with the preliminary observations made earlier, high proportions of nonbehavioral stops are clustered in the upper Bronx and western Brooklyn, where the proportion of Black residents is, for the most part, not particularly high. In contrast, where there are greater proportions of Black residents, notably in eastern Brooklyn and southeastern Queens, there are clusters of low proportions of non-behavioral stops. These findings might suggest that if there is a statistically significant relationship between proportion Black population and proportion nonbehavioral stops, it is likely in the opposite direction of what was proposed in hypothesis 1.

This section focused on an exploration of the geographic distribution of theoretically relevant variables. Beginning by illustrating the distributions of proportions of nonbehavioral stops, Black population, Latino population, and the designation as a high-crime area, I introduced what appears to be clustering of these characteristics. The

Moran's I and LISA statistic results indicate that there is strong evidence of spatial clustering of nonbehavioral stops at the neighborhood level. The results of these analyses suggest that neighborhoods experiencing especially high or low proportions of nonbehavioral stops are not distributed evenly across the city as would be expected if it were a statistically random phenomenon. I now turn to regression techniques to test if the frequency and proportion of nonbehavioral stops are related to other neighborhood characteristics.

Predicting Nonbehavioral Stops

   a. *Measuring the Effect of Neighborhood Characteristics on Nonbehavioral Stop Counts*

In this study, the central focus is how racial and ethnic compositions influences the occurrence of nonbehavioral stops. Model 1 is estimated with negative binomial regression to predict the number of nonbehavioral stops that occur in a census tract, based on theoretically significant neighborhood-level characteristics. The results of this analysis are presented in Table 3.

As Table 3 shows and as would be predicted based on prior literature, neighborhoods with great Black and Latino populations experience higher rates of nonbehavioral stops (p < .01). Accordingly, hypothesis 1, which predicted that the number of nonbehavioral stops in a neighborhood would increase as the proportion Black or Latino population increased, is supported. Furthermore, the magnitude of the coefficients of these variables is suggestive of the intensity with which stop and frisk policing is focused on minority neighborhoods. Per the reported incidence rate ratio, a 10% increase in the proportion of the neighborhood population that is Black leads to a

37% increase in the rate of nonbehavioral stops. The same increase in the proportion of

the population that is Latino results in an 6.8% increase in the nonbehavioral stop rate.

Table 3: Predicting Nonbehavioral Stop Rates Per Population (beta/se/irr) (n=25,123)	
Independent Variables (proportions)	
Population Black	1.55 ***
	(0.17)
	4.70
Population Latino	0.52 *
	(0.32)
	1.68
Population Asian	-1.30 ***
	(0.28)
	0.27
Population Other	5.83 ***
	(0.86)
	340.01
Stops Designated High Crime	0.05
	(0.05)
	1.06
Control Variables	
Proportion Males Age 16-24	-17.07 ***
	(2.48)
	0.00
Concentrated Disadvantage Index	0.15 *
	(0.08)
	1.16
Residential Instability Index	1.49 ***
	(0.10)
	4.43
Gini Coefficient	3.94 ***
	(0.89)
	51.59
Murder Rate per 1000 Population	-46.14 ***
	(11.53)
	0.00
Burglary Rate per 1000 Population	1.60 ***
	(0.40)
	4.97
Constant	-13.44 ***
	(1.46)
	0.00
R^2 = 0.11	
*p < 0.10 **p < 0.05 ***p < 0.01	

Although in line with prior research, it is also notable that all but one of the neighborhood-level control variables reach statistical significance (p < .01) in predicting occurrences of nonbehavioral stops. The small coefficients on the young, male population and murder rate, however, signal that the predictive ability of these measures have little practical meaning. As expected, concentrated disadvantage and residential instability increase the likelihood of stops occurring in a neighborhood. One surprising result is the effect of education. The number of stops is expected to decrease as the proportion of the population that has attended college increases. The results in Table 3 suggest, however, that nonbehavioral stops happen more frequently in neighborhoods with a more highly educated population. The only neighborhood characteristic that is not statistically significant is the perceived crime measure. One possible explanation is that stop rates are a result of where police are deployed, which may not be closely related to how officers perceive danger. This idea is support by the weak relationship between perceived crime and the reported crime variables.

b. *Measuring the Effect of Neighborhood Characteristics on Proportions of Nonbehavioral Stops*

Having illustrated that there is evidence of spatial clustering, the next question that must be addressed is whether, and to what extent, spatial clustering of nonbehavioral stops is associated with neighborhood characteristics. I use OLS regression to predict the proportion of nonbehavioral stops based on racial and ethnic composition, perceived crime rates, and other neighborhood-level characteristics. As described in the previous chapter, the problem of spatial autocorrelation is dealt with by using the calculated

egohoods values for all the neighborhood measures at the census tract level. The results for all models predicting the proportion of nonbehavioral stops are presented in Table 4. In each case, robust standard errors are reported. Model 2 provides a baseline assessment of the relationships between racial and ethnic composition and nonbehavioral stops. Model 3 integrates all of the predictor variables except for perceived crime.

When not controlling for other neighborhood characteristics, both the Black and Latino populations are significant predictors of nonbehavioral stops. However, in contradiction to hypothesis 2, the size of the Black population is negatively related to the proportion of nonbehavioral stops. However, once the other neighborhood characteristics are accounted for in Model 3, none of the racial and ethnic composition variables remain statistically significant. When controlling for other neighborhood characteristics, the racial composition of the neighborhood does not influence the proportion of stops that are nonbehavioral. With this finding, hypothesis 2 is not supported, as there is no evidence from this model that the proportion of nonbehavioral stops increases as the Black or Latino populations increase. The measure of concentrated disadvantage is significant (p <. 05) and negatively related to the outcome variable, such that a one unit increase in the concentrated disadvantage index results in a 2 percentage point decrease in the proportion of stops that are nonbehavioral. The murder and burglary rates are also statistically significant (p < . 01), albeit in opposite directions. While an increase in the murder rate leads to an increase in the proportion of nonbehavioral stops, an increase in the burglary rate has the opposite effect. The Gini coefficient is negatively related to the outcome variable (p < .05), indicating that as income inequality increases, the proportion of nonbehavioral stops decreases.

Table 4: Predicting the Proportion of Nonbehavioral Stops (beta/se)				
	Model 2	Model 3	Model 4	Model 5
Independent Variables (proportions)				
Population Black	-0.07 ***	-0.01	0.01	0.01
	(0.01)	(0.02)	(0.02)	(0.04)
Population Latino	0.04 ***	-0.03	0.00	0.00
	(0.01)	(0.04)	(0.04)	(0.04)
Population Asian	-0.16 ***	-0.03	0.00	0.01
	(0.01)	(0.04)	(0.04)	(0.04)
Population Other	0.09 **	0.08	0.04	0.05
	(0.04)	(0.09)	(0.09)	(0.09)
Stops Designated High Crime			-0.23 ***	-0.23 ***
			(0.01)	(0.01)
Control Variables				
Proportion Males Age 16-24		-0.19	0.10	0.13
		(0.35)	(0.33)	(0.33)
Concentrated Disadvantage Index		-0.02 **	-0.02	-0.02
		(0.01)	(0.01)	(0.01)
Residential Instability Index		0.02	0.01	0.01
		(0.01)	(0.01)	(0.01)
Gini Coefficient		-0.27 **	-0.19 *	-0.18
		(0.12)	(0.11)	(0.11)
Murder Rate per 1000 Population		7.38 ***	3.50 *	3.47 *
		(1.84)	(1.80)	(1.81)
Burglary Rate per 1000 Population		-0.26 ***	-0.12 *	-0.12 *
		(0.06)	(0.06)	(0.06)
Interaction Terms				
High Crime x Population Black				0.12 ***
				(0.04)
High Crime x Population Latino				0.00
				(0.05)
Constant	0.19 ***	1.30 ***	0.84 ***	0.71 ***
	(0.00)	(0.23)	(0.23)	(0.22)
R^2	0.02	0.16	0.24	0.24
N	25,539	25,123	25,123	25,123

$*p < .10$ $**p < .05$ $***p < .01$

Model 4 mirrors the previous model, except that it includes the high crime measure. The inclusion of the high crime measure boosts the predictive power of the model, suggesting that police officers' perceptions of neighborhood crime is an important variable in explaining the variance in nonbehavioral stops. Unsurprisingly, then, the high crime variable is significant ($p < .01$). The sign on the coefficient is negative, which means that as the perception of a neighborhood as dangerous increases, the proportion of nonbehavioral stops is lower. It is possible that police are more likely to discern people's behavior as suspect when they are in neighborhoods that they believe to be dangerous, which would account for the negative relationship here. However, the measures of racial and ethnic composition remain nonsignificant, again failing to provide support for hypothesis 2. Although the sheer numbers of nonbehavioral stops are greater in Black and Latino Neighborhoods, the reasons for stopping suspects do not appear to differ based on the racial composition of the neighborhood. Both official measures of crime remain significant ($p < .10$), indicating that police officers have different reasons for stopping suspects in neighbors with different levels of crime. The Gini coefficient also persists as a significant predictor of nonbehavioral stops ($p < .10$), suggesting that the reasons for stopping suspects are different in neighborhoods that are socioeconomically homogenous than they are in socioeconomically heterogeneous neighborhoods. Notable, too, is that concentrated disadvantage has lost its significance with the inclusion of perceived crime. In other words, once the level of perceived crime is accounted for, the reasons for which suspects are stopped no longer vary in relation to neighborhood-level socioeconomic status.

Model 5 builds on the previous two by adding interaction terms between the high crime variable and proportion Black and Proportion Latino. Although the interaction term between proportion Black population and perceived high crime results in significance ($p < .01$), the interaction with proportion Latino population does not. The significance of the interaction term suggests that the effect that proportion Black has on nonbehavioral stops is dependent on the extent to which a neighborhood is perceived by police officers as being high crime. This effect is visually represented in Figure 6 (Appendix A). Examining this graph, it is clear that when a neighborhood is not perceived as high crime, the proportion of residents who are Black matters more in determining the reason for a stop. As the perception of a neighborhood as a high-crime area increases, the size of the Black population matters less. This finding provides evidence to support hypothesis 3. However, contrary to what is predicted in hypothesis 2, proportion Black population is negatively related to the outcome, signifying that the proportion of stops based on appearance actually *decreases* in neighborhoods that are more predominantly Black. In comparison, the interaction term between Latino population and nonbehavioral stops is not significant, implying that the interplay between perception of crime and Black population is unique.

Finally, as in previous models, the Gini coefficient, murder rate, and burglary rate persist as significant predictors of nonbehavioral stops. The fact that the murder and burglary variables continue to maintain their significance even when controlling for other neighborhood characteristics, including the level of perceived crime, is indicative of how strongly reported crime influences policing practices. That the relationships of these two

measures of crime are related to nonbehavioral stops in opposite directions also accentuates the idea that different types of crime invoke different modes of policing.

In summary, this section reviewed the results from the first set of nested OLS regression models. Because the racial composition variables failed to reach statistical significance, no evidence was uncovered in support of hypothesis 2. The addition of the high crime variable increased the predictive power of the model significantly, signaling the importance of crime perceptions in explaining the reasons provided for stops. In addition, inclusion of an interaction term between perceived high crime and proportion Black population did result in significance, providing support for hypothesis 3. The next section presents results from the final two models, which estimates the proportion of "successful" behavioral and nonbehavioral stops.

Predicting "Success" of Nonbehavioral Stops

My final hypothesis addresses the issue of "successfulness" of stops. Specifically, hypothesis 4 predicts that the proportion of nonbehavioral stops that are "successful" will decrease as the Black population increases. To test this hypothesis, I ran OLS regression with the same independent variables used previously. In this case, the outcome variable of interest is the proportion of nonbehavioral (Model 6) or behavioral (Model 7) stops that are "successful". For this analysis, a stop is considered "successful" if the final result is arrest. The findings from these models are presented in Table 5.

As Table 5 shows, none of the measures of racial and ethnic composition reached statistical significance. This indicates that the "success" rates of nonbehavioral stops do not vary in accordance with proportion of the population that is Black or Latino. These results do not supply support for hypothesis 4. If "success" rates of nonbehavioral stops

Table 5: Predicting "Success" Rates of Stops (beta/se)		
	Model 6: Nonbehavioral Stops	Model 7: Behavioral Stops
Independent Variables (proportions)		
Population Black	0.00	-0.02
	(0.03)	(0.02)
Population Latino	-0.08	-0.03
	(0.05)	(0.03)
Population Asian	0.09	-0.02
	(0.06)	(0.02)
Population Other	-0.01	0.03
	(0.15)	(0.08)
Stops Designated High Crime	-0.01	-0.02 ***
	(0.01)	(0.01)
Control Variables		
Proportion Males Age 16-24	0.71 *	0.11
	(0.40)	(0.21)
Concentrated Disadvantage Index	0.00	0.00
	(0.01)	(0.01)
Residential Instability Index	0.01	0.02 **
	(0.02)	(0.01)
Gini Coefficient	-0.18	-0.08
	(0.15)	(0.09)
Murder Rate Per 1000 Population	4.52 **	5.86 ***
	(2.18)	(0.93)
Burglary Rate per 1000 Population	-0.16 **	-0.20 ***
	(0.08)	(0.03)
Constant	0.64 **	0.82 ***
	(0.27)	(0.12)
R2	0.09	0.13
N	25,003	25,003
*p < .10 **p < .05 ***p < .01		

were significantly lower in Black or Latino neighborhoods, it would suggest that

individuals in those areas are stopped based on lesser amounts of evidence of criminal

conduct. In contrast, the results of this model imply that police are similarly accurate in

assessing evidence of criminality, regardless of the racial composition of a neighborhood.

As in previous models, the measures of reported crime persist as significant predictors of

the outcome variable, albeit again in opposing directions. While nonbehavioral stops are

more "successful" in neighborhoods with higher murder rates, they are less "successful" in areas with high burglary rates. These results further suggest that crime is important in determining how police conduct their work. However, the results also indicate that level of perceived crime is not related to "success" rates of nonbehavioral stops. Model 6, which instead predicts "success" rates of behavioral stops, has similar results. In this case, none of the race variables reach statistical significance, but the three measures of crime all reach statistical significance ($p < .01$).

The absence of statistical significance among the racial and ethnic composition variables suggests that "success" rates of stops do not differ depending on the racial composition of a neighborhood. This finding is surprising, as prior studies have found that "success" rates are related to race (Gumbhir 2007; Geller and Fagan 2010; Ferrandino 2013). However, given the evidence, from this study as well as others, that nonbehavioral stop and frisk activity is more prevalent in areas of the city heavily populated by Black and Latino residents, a finding that "success" rates do not differ across neighborhoods still has practical significance and meaning. As demonstrated in the first model presented in this study, stop rates are higher in Black and Latino communities. If there are more officers in these neighborhoods who are policing more aggressively based on nonbehavioral characteristics than those in White areas, it is reasonable to expect that they would discover more crime. However, the results presented here suggest that this is not the case. Despite intensified surveillance in Black and Latino communities, officers

are encountering similar rates of arrestable offenses across all neighborhoods.

Chapter Summary

This chapter provided a detailed discussion of the findings of each of the analyses conducted for this study. I began by reviewing summary statistics and bivariate correlations between the dependent, independent, and control variables. I then moved on to an exploratory spatial analysis, which involved mapping out variables of interest, and then conducting the Moran's I and LISA statistics to verify the existence of spatial clustering of proportions of nonbehavioral stops. In the next section I discussed the results of negative binomial regression analyses, estimating how neighborhood characteristics affect counts of nonbehavioral stops. The findings of this model provided support for hypothesis 1. Next I proceeded through a series of three models that predicted proportions of nonbehavioral stops. The results of these models failed to provide support for hypothesis 2. However, they did illucidate the importance of perceived high crime in predicting variations in proportions of nonbehavioral stops, and the findings from model 3 did show support for hypothesis 3. Finally, I assessed the role of neighborhood characteristics in predicting "success" rates of behavioral and nonbehavioral stops. Because the coefficients on proportion Black and Latino failed to reach statistical significance, there was no support for hypothesis 4. In the final chapter, I will discuss the theoretical and practical significance of the findings presented here.

Chapter 6: Discussion and Conclusion

Discussion of Central Findings

This study sought to examine how neighborhood characteristics influence the reasons that police officers provide for stopping suspects, and how these patterns may reflect a perceived association between race and criminality. In doing so, this study attempted to make two notable contributions to the literature on policing. The first is its use of stop reasons as the dependent variable of interest. Most literature on police stops has analyzed the occurrence of stops, frisks, searches, arrests, or other stop outcomes, but we know little about why stops are initiated. By looking at the reasons that officers provide for stopping people, this study instead examined the process of suspicion formation, which occurs before a stop is made. Theoretically, this is a meaningful advancement. Analyses of stop outcomes are important because they may demonstrate racial disparities and provide evidence of systemic discrimination, and in doing so make conspicuous the need for policy reform. However, without assessing the mechanisms that are driving racial disparities, they provide little guidance as to what these changes should look like at the street level. In contrast, examining these pre-stop processes from the perspective of aggregate officer decision making provides insight into what drives racial disparities.

The second major contribution of this study is its focus on analyzing how neighborhood characteristics influence policing patterns. As discussed in the literature review, most policing research concentrates on the influence of suspect characteristics on police discretion, and researchers have lamented the absence of a similarly developed

literature investigating the effects of neighborhood context. Cultivating this line of inquiry is especially pressing, given that the research that has been conducted strongly suggests that neighborhood characteristics do influence how police officers engage in their work. Not only does these analyses corroborate the idea that neighborhood characteristics matter, but they also demonstrates that this is true when looking at macro-level policing patterns, as measured through the aggregation of decisions made by many police officers over time. Observing patterns across neighborhoods addresses the fact that communities are more than just a collection of individuals, and this provides a foundation to ask broader questions about social processes and ecological context.

The most informative finding from this study is that in perceived low-crime neighborhoods, the size of the Black population influences the reasons that police officers stop suspects. Specifically, a more predominant Black population leads to less behavioral stops net of other factors. In perceived high-crime areas, however, the size of the Black population does not appear to affect these decision making processes. On the other hand, the interaction between high crime area and Latino population produced no significant results, meaning that the proportion of the population that is Latino does not influence nonbehavioral stops, regardless of the perceived crime rate. Although this finding does not necessarily translate to evidence of racial discrimination, it does indicate that policing practices vary across neighborhoods with different racial compositions. Theoretically, this finding suggests that in areas of perceived low crime, policing practices differ depending on the size of the Black population. Furtheremore, that policing patterns differ depending on the racial composition of a neighborhood contradicts the claims of NYPD officials who claim that their policing practices are "color blind." If they were, we would

not expect to see patterns of policing that are related to the racial makeup of a neighborhood. These results also provide support for past research that has concluded that extra-racial neighborhood processes impact how police view the people in a neighborhood, regardless of their race or ethnicity (Reck 2014).

That neighborhood-level policing practices are racially and ethnically dependent was also evident from the results of the count model, which demonstrated that the rate of nonbehavioral stops is significantly higher in neighborhoods where a greater proportion of the residents are Black or Latino. Past studies have concluded that overall stop counts are higher in Black and Latino neighborhoods (Evans et al. 2014; Ferrandino 2014), and the results from this study may suggest that certain types of stops are driving this disparity. The higher stop rate of nonbehavioral stops in minority communities is likely, at least in part, a product of where police are stationed. In line with the literature on the criminalization of race and space (Stuart 2011; Lynch et al. 2013), the results of this analysis are indicative of departmental policies that mandate increased patrolling of minority individuals and the spaces in which they reside.

That so many more nonbehavioral stops are occurring in Black and Latino neighborhoods has immense practical consequences for both individuals and their communities. Because being stopped by police is positively and significantly related to later delinquency among adolescents (Wiley, Slocum, and Esbensen 2013), the higher frequency of stops in minority neighborhoods elevates the risk that young people in these communities will engage in criminal behavior. Given that nonbehvioral stops are conducted based on a person's appearance, rather than his or her behavior, it is plausible that the greater frequency of nonbehavioral stops is especially insidious in its

consequences. Being stopped when, quite literally, not doing anything wrong, might provoke greater hostility towards police and exacerbate tensions between police and the residents they monitor. Although a stop may involve only one individual, over time the cumulative effects of these negative interactions, not to mention possible outcomes such as arrest, begin to insidiously transform the nature of a community and its relationship to law enforcement (Roberts 2004).

The intention of categorizing stop reasons as either behavioral or nonbehavioral was to probe the question of the extent to which minority status at the neighborhood level is, in itself, associated with criminality. My conjecture was that if Black and Latino Communities are broadly perceived of as criminal, then police officers may transfer this perception onto individuals' appearances. The consequence of this process would be that a physical characteristic that does not arouse suspicion in a different context, such as a predominantly White neighborhood, may be attributed a criminal character in a Black or Latino neighborhood. The hypothesized relationship in this study rested on the findings of past research, which established that the percentage of a neighborhood's population that is Black or Latino is positively associated with perceived crime rates and fear of victimization. Positive and significant findings in this study would have suggested that police are more likely to ascribe suspicion based on appearance when surrounded by Black or Latino citizens; however, the findings did not confirm this conjecture. It is possible that the operationalization of concepts in this study does not accurately capture the underlying mechanisms driving the reasons that stops are conducted. A different process could be taking place in which the association between minority communities and crime actually compels police officers to be more likely to interpret behavior as

indicative of criminal activity. If this is the case, analyzing behavioral stops may provide a better framework for deciphering divergent patterns in stop reasons across racially differentiated neighborhoods. Alternatively, the absence of statistically significant findings among the race variables may have been a result of the very conservative operationalization of nonbehavioral stops, which excluded any stop that included even a single behavior-based reason.

Another important finding of this study is that patrolling in a neighborhood that is perceived to be dangerous makes officers less likely to make stops based on appearance alone, and perhaps more likely to discern behavior as criminal. That inclusion of the high crime variable boosted the predictive power of the model so appreciably indicates how important it is to predicting variance in proportions of nonbehavioral stops, and understanding patterns of stop reasons more generally. The results of this analysis suggest that neighborhoods that are considered high crime experience lower proportions of nonbehavioral stops. If officer perceptions of crime are in line with actual crime rates, this relationship makes sense, as there is likely more visible crime taking place, or, at least, reason to believe that people's behaviors are criminally related. However, as noted in the previous chapter, the bivariate relationships between the high crime variable and the reported measures of murder and burglary are quite weak, which brings into question how accurately officer perceptions of crime reflect reality. One possible explanation for this pattern is that in a perceived high crime area, officers may feel like it is a waste of time to stop someone based on their appearance if they suspect actual crimes are actively taking place.

The findings also suggest that different types of crime compel police to invoke dissimilar types of patrolling strategies. Although the murder and burglary rates are both significant predictors of the proportion of nonbehavioral stops, they relate to the dependent variable in opposite directions. In other words, while a higher murder rate leads to higher proportions of nonbehavioral stops, a higher burglary rate leads to a lower proportion. This pattern stipulates that the relative prevalence of violent crimes and property crimes influences how police view a neighborhood and, consequently, how they conduct their duties. This is theoretically important to research on policing, as it signifies the limitations of including only a single indicator of crime. The contrasting effects of murder and burglary rates may be attributable the differential natures of those crimes. If murders are concentrated in neighborhoods where there is recurrent gang or drug-related violence, police may be more familiar with the residents and regular criminal actors. It is worth recalling that one of the nonbehavioral reasons for a stop is that a suspect "matches a relevant description." If police are stopping people who they know to be generally involved in crime, this may lead to a higher proportion of nonbehavioral stops.

The final variable that was consistently statistically significant was the Gini coefficient of income inequality. Prior research has argued that income inequality is a better predictor of crime than other socioeconomic measures (Hipp 2007). Grounded in relative deprivation theory, the posited relationship is based in the idea that individuals compare themselves to those around them, and respond deviantly if they feel they have not been granted their fair share of resources. In this analysis the Gini coefficient sustains significance while the measure of concentrated disadvantage does not, providing evidence that this claim is also true in predicting policing patterns. A similar process may

be occurring wherein police officers judge residents in comparison to their neighbors, thus causing them to patrol in socioeconomically heterogeneous differently than in socioeconomically homogenous neighborhoods. Other studies have found this to be the case when adjacent neighborhoods differ in their racial composition (Vera Sanchez and Rosenbaum). The findings of this study indicate that as income inequality increases, the proportion of nonbehavioral stops decreases. The meaning of this relationship is complicated to disentangle, because income homogeneity simultaneously includes neighborhoods characterized by concentrated disadvantage and those characterized by concentrated privilege. It is possible, perhaps probable, that there are different mechanisms leading to higher proportions of non-behavioral stops in these two opposing types of neighborhoods. This is a relationship that should be evaluated further.

In contrast to what I predicted, the "success" rates of nonbehavioral stops showed no relationship to the racial and ethnic composition of neighborhoods. This suggests that officers make nonbehavioral stops based on equally appropriate levels of suspicion across neighborhoods, regardless of the race or ethnicity of the residents. These results diverged from past research, which has found that the "success" of stops is connected to race (Gumbhir 2007; Ferrandino 2013; Geller and Fagan 2010). The lack of significant findings may be in part a consequence of how "success" was operationalized. It could be that a more appropriate way to assess success rates is by only analyzing stops in which a frisk or search occurred. If either a frisk or search results, it suggests that a heightened level of suspicion has been reached, beyond simply finding someone's behavior or appearance out of place.

As in the previous results, the three measures of crime continued to be consistent predictors, but again opposing directions. While the murder rate is positively related to "success" rates, the burglary rate and perceived high crime are negatively related to them. The positive correlation in the former relationship may be explained by the relatively greater severity of crimes taking place. That "success" rates are slightly lower in neighborhoods considered to be dangerous makes sense, in that if officers believe they are in a high-crime area, their suspicion may be heightened, thus causing to them to initially sense trouble where there actually is none.

Study Limitations

This study, of course, has its analytic limitations. The most salient limitation in this study is the measurement of the dependent variable. First, the stop reasons provided on the UF-250 are themselves quite vague. Explaining that a stop was conducted because a suspect had a "suspicious bulge" or exhibited "furtive movements" leaves much to be desired. Without a more in-depth description of what aroused suspicion, it is difficult to interpret what the suspicion suggests. Second, because the officers are simply checking off boxes on a form, it is difficult to know to what extent the reasons they provide actually match the process of suspicion formation. This is especially true in light of prior research suggesting there may be "narratives of suspicion" that NYPD officers follow in order to meet constitutionally established criteria of reasonableness (Fagan and Geller 2015). Having access to more elaborate explanations of why stops are conducted, would allow for a more nuanced analysis of the processes at play. The fact that UF-250 forms are completed after a stop has been completed in its entirety also introduces measurement error into the dependent variable. Officers may inaccurately recall their reasons for

making a stop, or, alternatively, purposefully change the reasoning after the fact in order to make stops appear more legitimate.

Also limiting is the lack of organizational knowledge, especially regarding how police officers are dispersed across the city. In this study, organizational controls were limited to the incorporation of dummy variables designating the precinct to which each census tract belongs. It is likely that some neighborhoods experience more stops than others because there are simply more police officers in the area. "Hot spot" policing, where law enforcement is concentrated in certain "problem" areas has been a central element of stop and frisk policing (Kelling and Coles 1998), most recently in the form of Operation Impact (New York City 2010). Knowing how officers are geographically distributed would provide insight into how the NYPD perceives of physical space across the city and would allow for an additional level of control within statistical models. Additionally, having information about how patrol officers are actually directed to conduct their work would allow for direct testing of the effects of department policy.

To account for spatial autocorrelation in these analyses, I used the egohoods technique. To do this, an egohoods version of every neighborhood measure from the ACS was created for each census tract by averaging the values of all the census tracts within a 2 mile radius. A radius of 2 miles had to be employed in order to ensure that all census tracts had at least one "neighbor" to include in this calculation. However, in the context of New York City, parts of which are geographically small with exceptionally high population densities, conceptualizing a neighborhood as spanning 4 miles across is likely a poor measure of a community. To address this problem, future studies may test out using radii of varying distances, more suitable to the geography of New York City.

A final limitation is the use of precinct-level crime data as an estimate of neighborhood-level crime. The persistent statistical significance of the crime variables indicate how important these measures are in examining variation in stop reasons across neighborhoods. However, a police precinct consists of many census tracts, and I was thus not able to realistically capture how crime varies across space. Accordingly, census-tract level crime data would allow for an even more accurate analysis of the effects of reported crime.

Directions for Future Research

This study sets a foundation for further neighborhood-level research on stop and frisk policing in New York City. This study used a particular paradigm to characterize individual stops by labeling them as either behavioral or nonbehavioral. Although racial composition did not prove to be a significant predictor of the proportion of nonbehavioral stops, it would be worth exploring the relationship between racial composition and other narratives of stop reasons. One option would be to instead analyze stops based on behavior, rather than appearance. If behavior is more likely to be perceived of as criminal in Black neighborhoods, as may be construed from this study, perceptions of behavior may be a better indicator of how policing varies across communities. An alternative technique would be to analyze stop reasons individually. In this study, stop criteria including "fits a relevant description," "wearing clothes commonly used in a crime," and "suspicious bulge" were all collapsed into a single category. It is possible that they individually capture different processes of suspicion formation.

Future research might also explore how changing demographics influence policing practices in a neighborhood. Some studies have concluded that dynamic

measures of neighborhood racial composition, such as the percent increase of the Black or Latino population, are better predictors of fear of crime than static measures (Kane 2002; Culver 2004). In light of recent gentrification in certain parts of New York City, notably Brooklyn, and the swift fluctuation in racial composition that follows, such an analysis would be very relevant to the realities of a changing demographic landscape. It could also potentially provide insight regarding the speed with which policing practices, and perhaps official policy, can change to adapt to a new setting.

Conclusion

In the sole dissenting opinion in *Terry*, Supreme Court Justice Douglas lamented the ascendency of police power, explicitly acknowledging that in its decision the Court granted police "greater authority to make a 'seizure' and conduct a 'search' than a judge has to authorize such action" (Terry v. Ohio 1968). Power of this nature necessitates external assessment to ensure that it is exercised appropriately. In the context of proactive policing, which inevitably implicates innocent people, understanding why people are stopped on the street is one way of examining whether, and to what extent, law enforcement is being justly applied.

The foremost finding of this study is that neighborhood characteristics influence macro-level policing practices. The results of the analyses conducted provide evidence that the perceived and reported levels of crime within a neighborhood lead patrol officers to conduct stops for different reasons. The formation of suspicion has racial and ethnic implications, as well. Specifically, in neighborhoods that are not considered dangerous, the reasons that officers make stops differ depending on the relative size of the Black population.

The patterns in this study are suggestive of the cumulative influence of individual stops over time. As policing agencies construct policies to address crime, it is integral that they recognize the expansive effect of proactive policing. Although a stop may implicate only one individual, the collective effect of many stops over time implicates whole communities. If the goal of proactive policing is to protect communities from danger, police have a responsibility of ensuring that that is the true effect.

Appendix A: Figures

Figure 1: Proportion Nonbehavioral Stops
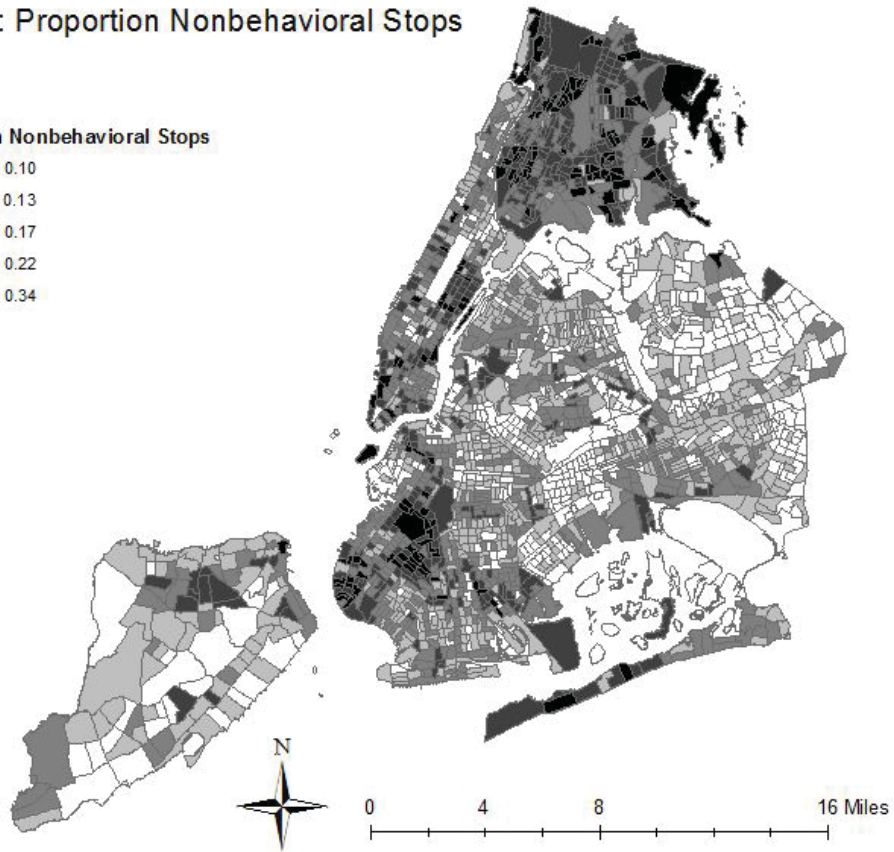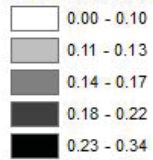
Figure 2: Proportion Black Population

Proportion Black Population
- 0.00 - 0.10
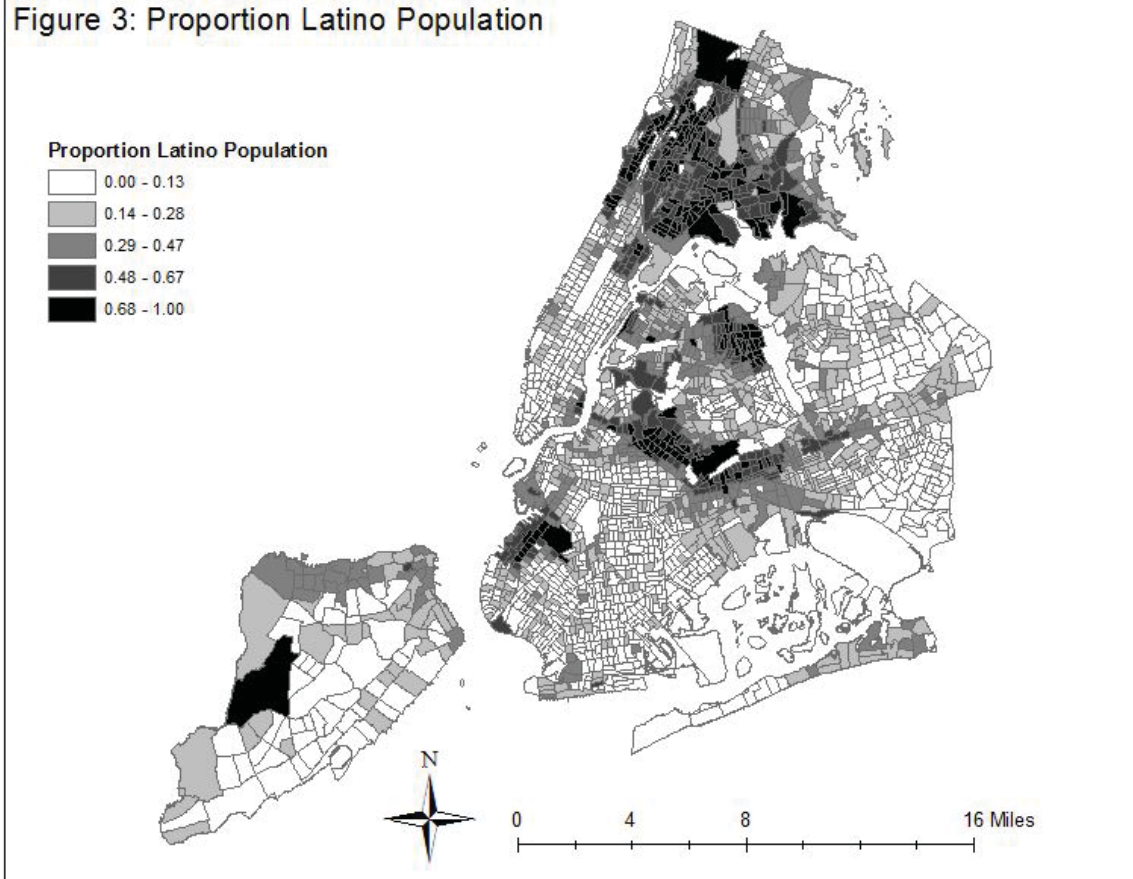- 0.11 - 0.28
- 0.29 - 0.49
- 0.50 - 0.72
- 0.73 - 1.00
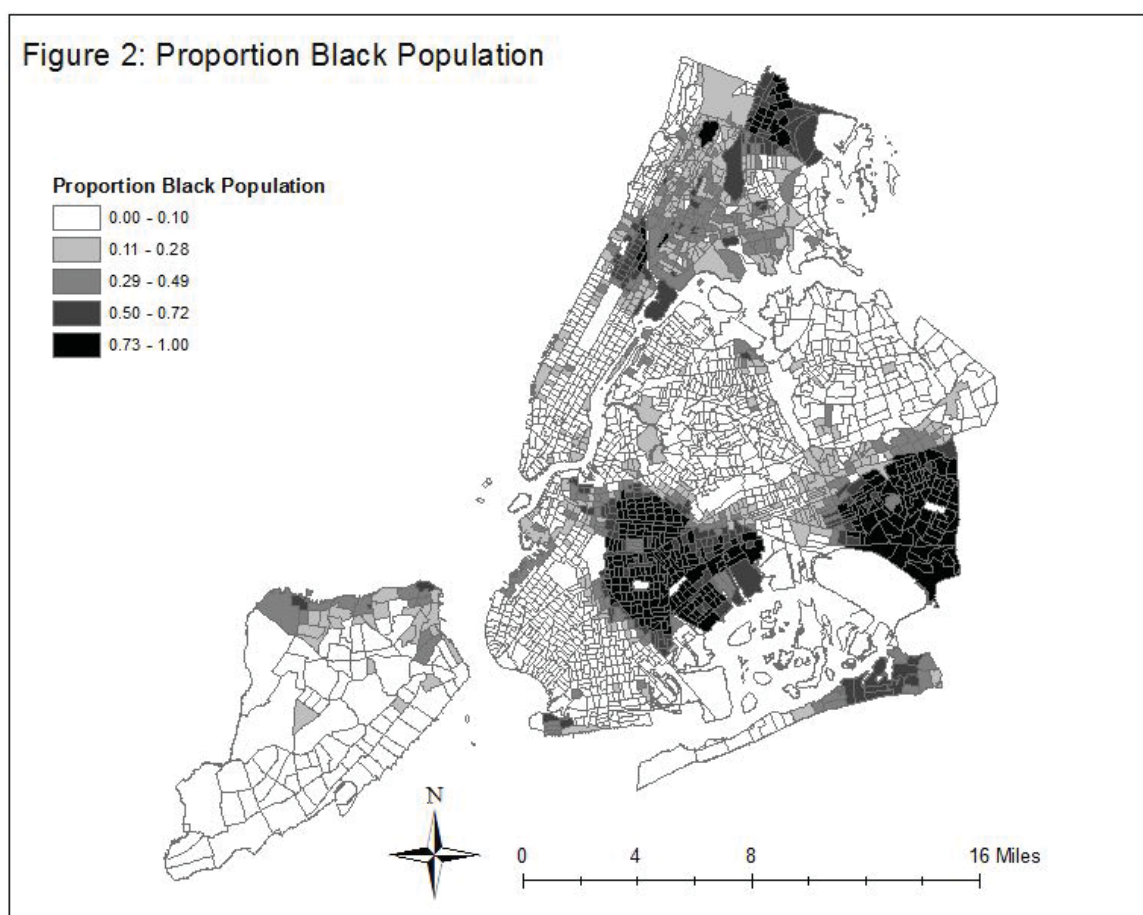
Figure 3: Proportion Latino Population

Proportion Latino Population
- 0.00 - 0.13
- 0.14 - 0.28
- 0.29 - 0.47
- 0.48 - 0.67
- 0.68 - 1.00

Figure 4: Proportion of Stops Designation as Occurring in a High-Crime Area

High-Crime Designation
- 0.18 - 0.41
- 0.42 - 0.49
- 0.50 - 0.56
- 0.57 - 0.63
- 0.64 - 0.83
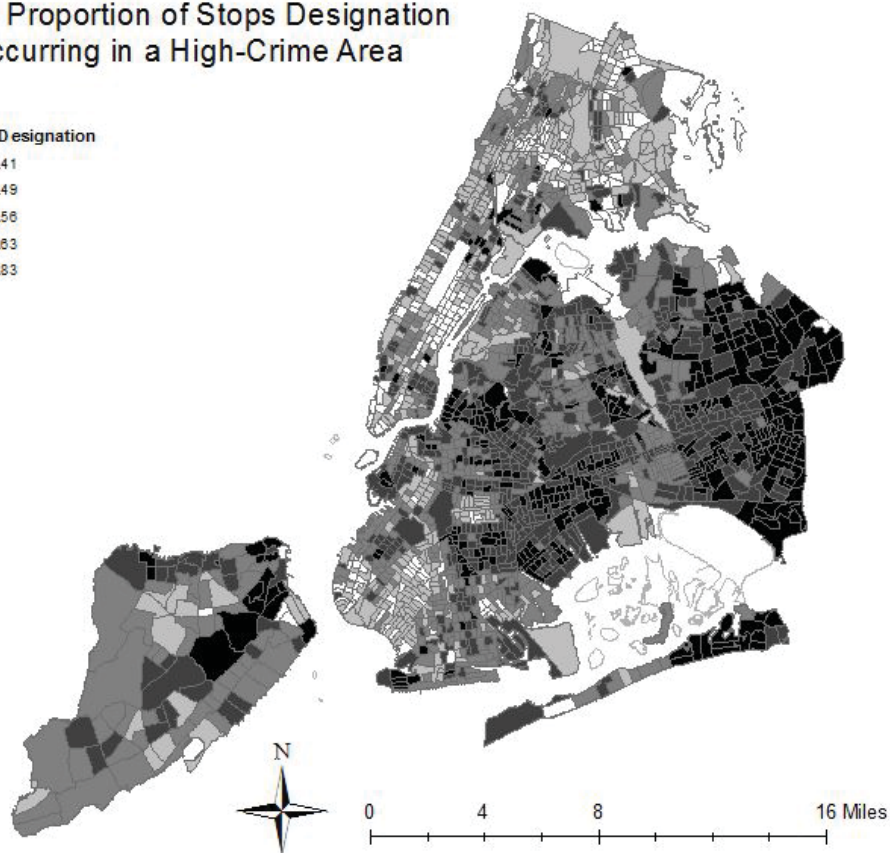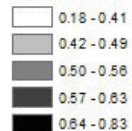
Figure 5: Clustering of Nonbehavioral Stops

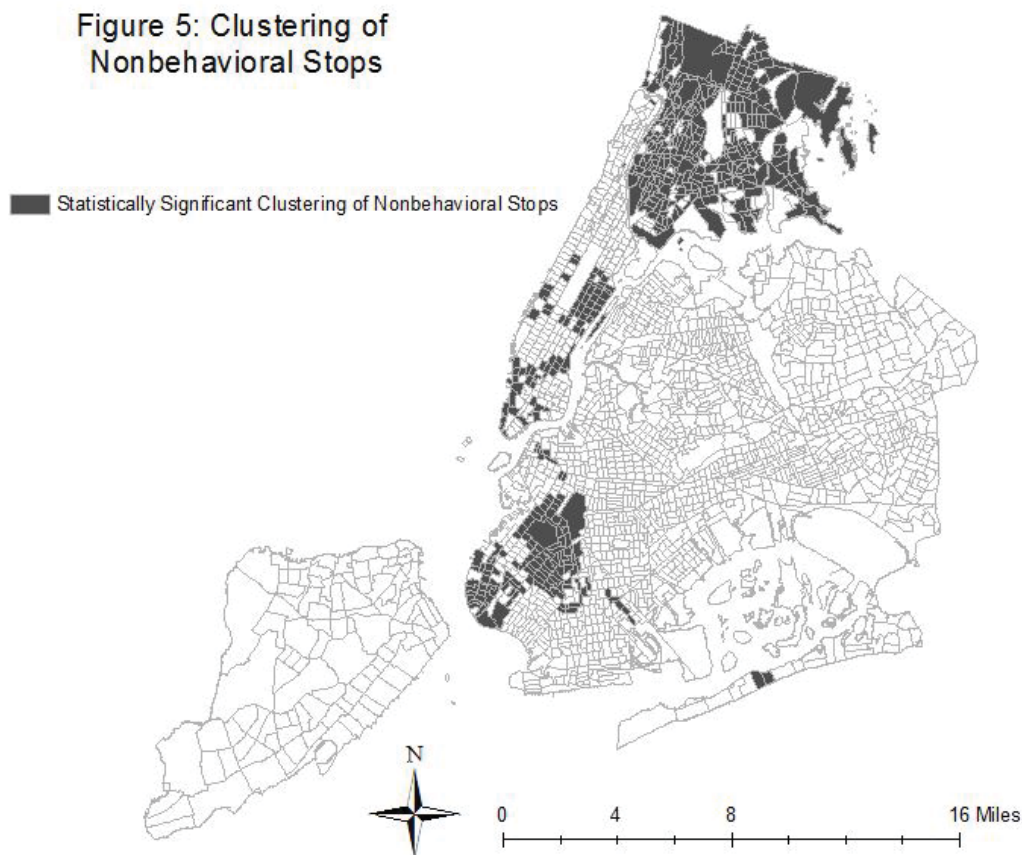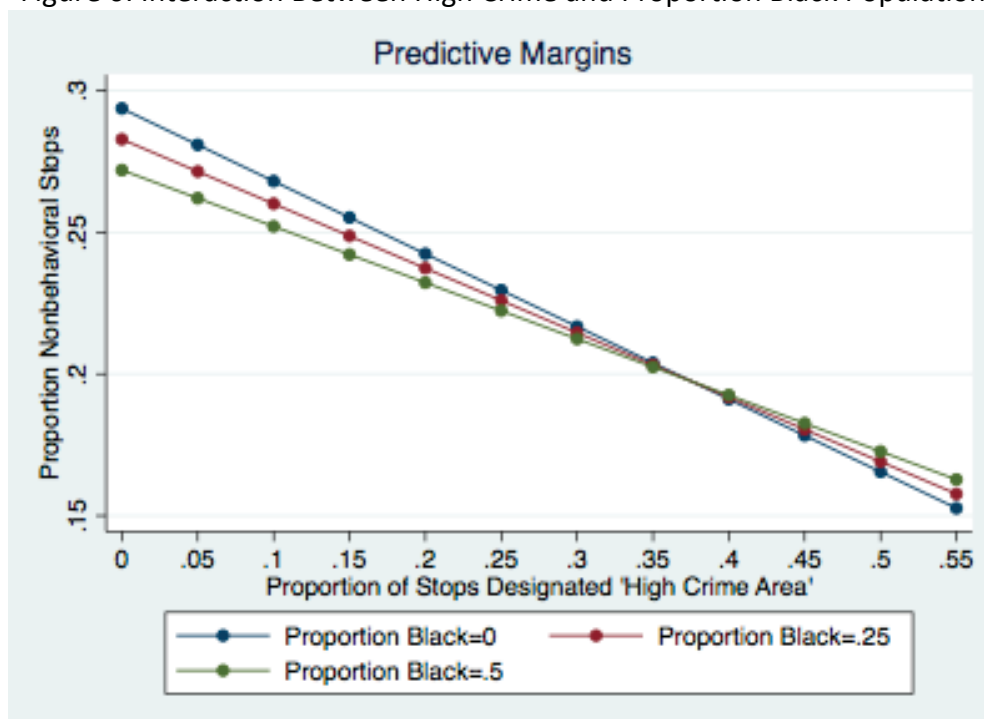Statistically Significant Clustering of Nonbehavioral Stops

Figure 6: Interaction Between High Crime and Proportion Black Population

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